COOPERATIVE AND NON-COOPERATIVE DECISION BEHAVIORS IN RESPONSE TO THE INSPECTION AND MAINTENANCE PROGRAM IN THE ATLANTA AIRSHED, 1997-2001

A Dissertation
Presented to
The Academic Faculty

By

Asim Zia

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

Georgia Institute of Technology

July 2004

COOPERATIVE AND NON-COOPERATIVE DECISION BEHAVIORS IN RESPONSE TO THE INSPECTION AND MAINTENANCE PROGRAM IN THE ATLANTA AIRSHED, 1997-2001

Bryan G. Norton (Chair)
Michael O. Rodgers
Barry Bozeman
Leisha DeHart-Davis
Douglas S. Noonan

Date Approved: July 11, 2004

EPIGRAPH

The tension between normative approaches, which are constantly in danger of losing contact with social reality, and objectivistic approaches, which screen out all normative aspects, can be taken as a caveat against fixating on one disciplinary point of view. Rather, one must remain open to different methodological standpoints (participant vs. observer), different theoretical objectives (interpretive explication and conceptual analysis vs. description and empirical explanation), the perspectives of different roles (judge, politician, legislator, client, and citizen), and different pragmatic attitudes of research (hermeneutical, critical, analytical etc.) Habermas (1998: 6-7).

ACKNOWLEDGEMENTS

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AHP	The Analytic Hierarchy Process
AIR	Air Injection Reactor system
AQL	Air Quality Laboratory
BTS	Bureau of Transportation Statistics
CAFE	Continuous Atlanta Fleet Evaluation
CARB	California Air Resources Board
CLL	Closed Loop Combustion Control
CO	Carbon Monoxide
CO_2	Carbon Dioxide
EGR	Exhaust Gas Recirculation
ELECTRE	Elimination et choix traduisant la realite
EMFAC	California Air Resources Board Emission Factor Model
EPA	Environmental Protection Agency
EU	Expected Utility Hypothesis
EV	Expected Value Hypothesis
GA-DMVS	Georgia Department of Motor Vehicles and Safety
GA-DNR	Georgia Department of Natural Resources
GA-EPD	Georgia Environmental Protection Division
GG^{-1}	Grams per US Gallon
GLM	Generalized Linear Model
HC	Hydrocarbon
IM	Inspection and Maintenance Program
IMRC	Inspection and Maintenance Review Committee in California
MCDM	Multiple Criteria Decision Making Model
MDM	Meta-Decision Model
MOBILE	Environmental Protection Agency emission-factor model
MSA	Metropolitan Statistical Area
MY	Model Year
NO	Nitric Oxide
NO_2	Nitrogen dioxide
NOx	Oxides of Nitrogen
NRC	National Research Council
OBD	On Board Diagnostic Systems
OLS	Ordinary Least Squares regression model
OXY	Oxidation (two-way) catalyst
PCV	Positive Crankcase Ventilation System
PPP	Polluter Pays Principle
RCT	Rational Choice Theory
RSD	Remote Sensing Data
TAC	Thermostatic Air Cleaner
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TWC	Three Way Catalyst
USA	United States of America
VIN	Vehicle Identification Number
WLS	Weighted Least Squares regression model

SUMMARY

When confronted with decisions involving provision of environmental resources, do individuals in a society act in non-cooperative and selfish ways or do they behave cooperatively and altruistically? Controlled lab studies in experimental economics have found that people are neither perfectly cooperative nor perfectly non-cooperative for provision of public goods under the contextual conditions of voluntary mechanisms. In contrast, this study employs a field experimental methodology to investigate the cooperative and non-cooperative decision behaviors of high-emitting vehicle owners in the Atlanta airshed that arose under the contextual conditions of the Inspection and Maintenance (IM) regulatory mechanism designed for the provision of clean air.

Previous studies show that the largest potential reductions in vehicular tailpipe emissions from the Clean Air Act Amendments 1990 mandated regulatory mechanisms, such as Atlanta's IM program, are associated with a small number of high-emitting vehicles. A recent National Research Council report recommended that more research is needed to evaluate the impact of cooperative and non-cooperative decision behaviors of high-emitting vehicle owners on the on-road vehicular emissions. This study also evaluates the impact of cooperative and non-cooperative decision behaviors of high-emitters on vehicular tail-pipe emissions of ozone pre-cursors -- such as Carbon Monoxide (CO), Hydrocarbons (HC) and Oxides of Nitrogen (NOx) -- in Atlanta between 1997 and 2001.

Environmental regulatory mechanisms, such as Atlanta's IM program, mostly share one common assumption that is known as the polluter-pays-principle (PPP): polluters should pay the cost of clean-up to maintain the environmental quality standards enshrined in specific regulations. While arguably PPP may be equitable in regulating pollutant emissions from stationary sources of pollution, such as industrial plants, it can be hypothesized that PPP is unfair in the case of environmental regulations aimed at mobile sources of pollution, such as high-emitting vehicle owners. More specifically, the following hypotheses are tested: (1) High-emitting vehicle owners, as detected by IM program regulations, have significantly higher odds of residing in lower income and African-American-dominated census block-groups as compared to the normal emitting vehicle owners. (2) IM program intervention is unfair because it forces lower income and

racial minority groups to pay an inordinate share of the environmental pollution clean-up costs for maintaining clean air in Atlanta.

Remote sensing data of a random sample of approximately 1.42 million vehicles observed on-road inside the IM program boundaries between 1997 and 2001 are matched with IM program data and vehicle registration data to identify the cooperative and non-cooperative high-emitting vehicle owners. Normal emitters are treated as a control group. The research uses multiple, statistical decision-theory models, including both linear and non-linear regression analysis, to estimate the impact of cooperative and non-cooperative behavioral strategies of high-emitters on vehicular tail-pipe emission factors, CO, HC and NO, during the study period. A mixed-pool time-series analysis is carried out to estimate changes in the vehicular tail-pipe emissions from year to year due to the decision behaviors of high-emitting vehicle owners during the study period.

The addresses of the sampled vehicle owners are geo-coded and information about socio-economic parameters of vehicle owners at the census block-group level is collected from the 2000 census data. A multinomial logistic regression model is employed to test the hypotheses concerning the systematic variation in socioeconomic and demographic conditions of vehicle owners in the cooperative, non-cooperative and control groups. In addition, an ecological regression model is used to test differences in the median household income of the vehicle owners at the census block-group ecological level in the Atlanta airshed.

Approximately 42% of the high-emitting vehicle owners are found to be cooperative and 58% non-cooperative. The social theory that individuals behave cooperatively appears to be farther from the truth under the contextual conditions of regulatory mechanisms. On the other hand, the game theoretical assumption that individuals behave selfishly is rejected but still appears to be holding for 58% of the decision makers. From the perspective of environmental policy, cooperative behaviors of 42% of high-emitting vehicle owners in the Atlanta airshed caused a decreased production of 47% in HC emission factors during 1997 and 2001. Surprisingly, there is no statistical difference between the CO and NO emission factors of vehicles owned by cooperative and non-cooperative high-emitters in the Atlanta airshed. This surprising result suggests that the repairs of emission control systems carried out by cooperative vehicle owners are not durable enough over a period of five years in reducing CO and NO emission factors.

Results also suggest that environmental regulations should not assume PPP under all contexts because the IM program in the context of Atlanta is inequitable. The IM program targets high-emitting vehicle owners who live in relatively lower median household income areas as compared to the normal emitting vehicle owners in the Atlanta airshed. Regulations should be context-sensitive. Cost-sharing mechanisms for pollution clean-up, rather than PPP alone, may prove to be more effective and fairer in some contexts, such as for high-emitting vehicle owners and other mobile sources of environmental pollution. Changes in the current IM program could improve air quality. Such changes include improving vehicle registration laws and IM program rules, such as disallowing IM test failures from registering anywhere in the state of Georgia and requiring an emissions test on every change of vehicle ownership inside the 13-county IM program area, creating better incentive mechanisms for high-emitting vehicle owners, and discussing new policy alternatives with non-cooperative vehicle owners. The evidence from this study is expected to aid relevant decision-makers to adapt the incentive mechanisms of IM programs, in particular, and environmental regulations, in general, so that public policies are both more effective and equitable in their societal impacts.

Keywords: decision behavior, environmental policy, meta-theory, program evaluation, air quality.

CHAPTER 1

INTRODUCTION

1.1 The objectives of the study

This study investigates three interconnected research questions: First, do people decide to behave selfishly or cooperatively with societal regulations for the provision of environmental resources such as clean air? Second, if they decide to behave selfishly, what is the resulting impact on the provision of environmental resources; and if they decide to cooperate, is the provision of environmental amenities significantly increased or not? Third, what are the socio-economic contextual conditions that affect the odds that some decision makers will be more cooperative than others? Or, conversely, do non-cooperative decision makers face socio-economic contextual conditions that systematically differ from the cooperative decision makers?

More specifically, a quasi-experimental research design is used to evaluate the cooperative and non-cooperative decision behaviors of high-emitting vehicle owners in the Atlanta Airshed from 1997 to 2001. The cooperative and non-cooperative decision behaviors emerge in response to the 1990 Clean Air Act Amendments' mandated policy intervention known as Vehicle Inspection and Maintenance (IM) program. The limitation of the scope to the Atlanta airshed helps in focusing on the contextual conditions of individual decision makers in a regional framework. It also allows modeling the impact of cooperative and non-cooperative decision behaviors of high-emitting vehicle owners on the outcomes of vehicular tail-pipe emissions, especially Carbon Monoxide (CO), Hydrocarbons (HCs) and Oxides of Nitrogen (NOx). Another advantage in limiting the scope is that it allows analysis at a finer geo-spatial resolution to test whether cooperative and non-cooperative vehicle owners come from systematically different socio-economic and demographic contexts.

The issue of cooperative and non-cooperative decision behavior has been an active research agenda among game theoreticians (Carraro and Siniscalo 1992; Carraro and Siniscalo 1993; Chander and Tulkens 1992; Lehmann 2000; Ostrom 1990; Ostrom 1999; Ostrom 2000; Petrosjan and Mazalov 2000; Scharpf 1997), social psychologists

(Axelrod 1980; Axelrod 1984; Rapoport 1989), experimental economists (Gintis 2000; Kagel and Roth 1995; Ledyard 1995; Schmidtz 1991; 1993), sociologists (Marwell 1982), political scientists (Orbell and Dawes 1991; Ostrom and Walker 1991) and evolutionary biologists (Kauffman 1993; Kauffman 1995; Maynard Smith 1982). Game theorists start from the foundational assumption that humans behave selfishly and thus they predict that selfish players will not cooperate with community-mandated environmental regulations if there are other non-cooperative and free-riding strategies that dominate the (subjective) expected-utility of cooperative strategies available to the players. The Nash equilibrium solution, for example, predicts the domination of non-cooperative behavioral strategies in public goods games, which leads to famous prisoner's dilemma situations, such as Hardin's tragedy of commons (Hardin 1968; Hardin 1982) and Sen's description of selfish agents as rational fool (Sen 1999). On the other hand, some political scientists and sociologists argue that cooperative decision behavior is perfectly rational and understandable in the context of human societies because humans cherish values that cannot be exactly translated into a *linear* utilitarian calculus. Ledyard (1995: 121) summarizes the current crisis in decision theoretical research posed by the fundamental behavioral question whether people are selfish or cooperative:

"The debate has been long-standing with much heat and little light. Economists and game-theorists argue that the hypothesis of selfish behavior is the only viable one as an organizing principle, yet they also contribute to public television and vote in elections. Sociologists and political scientists argue that societies are naturally cooperative through the evolution of social norms or altruism. Preconceived notions bordering on the theological have sometimes been rejected by data. But those who are reluctant to part with cherished theories have in turn rejected the data. Disciplinary boundaries have been drawn, breached, and redrawn. It is into this fray that experimentalists have come, trying to generate light where previously there was little."

Results from previous experimental studies, mostly conducted under controlled laboratory conditions of voluntary mechanisms, suggest that human agents neither behave perfectly selfishly nor perfectly cooperatively (Gintis 2000; Ledyard 1995). After reviewing the state-of-the-art experimental research conducted to estimate the cooperative and non-cooperative decision behaviors for provision of public goods under voluntary mechanisms, Ledyard (1995:172-173) states: "There appear to be three kinds

2

of players: dedicated Nash players who act pretty much as predicted by game theory with possibly a small number of mistakes, a group of subjects who will respond to self interest as will Nash players if the incentives are high enough but who also make mistakes, and respond to decision costs, fairness, altruism, etc., and a group of subjects who behave in an inexplicable (irrational?) manner. Casual observation suggests that the proportions are 50 percent, 40 percent, 10 percent in many subject pools". Ledyard is however quick to qualify this statement by stating: "…of course, we need a lot more data before my outrageous conjectures can be tested."

The previous experimental results have shifted the emphasis of current research in game theory, experimental economics, political science and social psychology; the question about cooperative and selfish behavior has now been reformulated as follows: under what contextual conditions do people behave cooperatively or selfishly? Ledyard (1995: 143) provides a list of individual level contextual conditions that experimentalists, coming from various disciplinary perspectives, have hypothesized to have significant effect on individual decision behaviors under voluntary mechanism environments. The contextual conditions include marginal per capita return, numbers of players, repetition, common knowledge, gender, homogeneity, thresholds, beliefs, economics training, experience, friendship/group identification, learning, altruism/fairness, effort, risk aversion, communication, rebates, unanimity and moral suasion. On the other hand, empirical theorists in social psychology (Rapoport 1989) and political science (Boyd and Iversen 1979) have hypothesized that it is not only the individual level attributes of decision makers but also the group level contextual conditions, such as community level socio-economic characteristics, that affect the behavior of decision makers.

While the controlled laboratory experiments have their own advantages and dis-advantages in assessing cooperative and non-cooperative decision behaviors, as well as the contextual conditions of cooperative and non-cooperative decision makers, quasi-experimental field studies present another set of research methodologies to assess cooperative and non-cooperative decision behaviors. Controlled laboratory experimental studies usually focus on modeling "voluntary mechanisms" for assessing cooperative and non-cooperative decision behaviors. By contrast, this study employs a quasi-experimental research methodology to examine cooperative and non-cooperative decision behaviors under the actually implemented "regulatory mechanism" of the IM program in the Atlanta airshed.

A quasi-experimental research design also enables the testing of hypotheses about cooperative and non-cooperative decision behaviors from a meta-decision theoretical perspective in actual field settings, whereby public policy interventions are treated as experimental in nature (Cook and Campbell 1979; Norton 1999; Norton and Steinemann 2001). In the language of controlled laboratory experimentalists, the meta-decision theoretical perspective will allow one to compare "regulatory mechanisms" with other forms and theories of governance, including voluntary, market or adaptive mechanism designs.[1]

If meta-decision theory is defined as a second-order meta-theory of various decision theories, then meta-decision theoretical research investigates in a larger frame the ontological commitments and foundational assumptions made by first-order decision theories. For example, Rational Choice Theory (RCT) is concerned with predicting the rational courses of actions that ought to be taken by rational individuals who fulfill certain axiomatic assumptions, such as that rational agents should have complete, transitive and consistent preferences over the outcomes resulting from all the available courses of actions and events (Raiffa 1968; Rapoport 1989). On the other hand, John Rawls' theory of justice is concerned with finding if a *well-ordered* society is promoting the good of its citizens, and if it is regulated by a public conception of justice (Rawls 1971). Taken alone RCT, or the Rawlsian theory of justice, cannot critically review its own ontological commitments or foundational assumptions from *within* its theoretical boundaries. Nor can first-order decision theories internally justify the relevance of their ontological commitments for a variety of decision behaviors encountered in the broader public sphere.

By their very own ontological commitments, RCT and Rawl theory of justice are examples of "normative" decision theories, unlike the "bounded rationality theory" of Simon (1982), the "prospect theory" of Kahneman and Tversky (1979) and the "Fuzzy theory" of Zadeh (1965), because these last three theories are examples of "descriptive" decision theories. First-order decision theories have different ontological commitments and traditionally they have been partitioned in normative and descriptive categories (Kahneman and Tversky. 1988; Rapoport 1989). It is important for evaluating public-sphere decision behaviors that the ontological commitments of first-order decision

---

[1] In chapter 2, I present a generic model of incentive mechanism designs and show how regulatory mechanisms differ from voluntary, market and adaptive mechanisms.

theories are duly considered before employing the framework of any one theory to test empirical hypotheses about human decision behaviors in real-world situations. In order to properly employ first-order decision theories as delimited by their ontological commitments and foundational assumptions, meta-decision theory critically analyzes first-order decision theories from external, second-order level, meta-theoretical perspectives (Carnap 1950; Habermas 1998; Norton 1977). While a grand-world application of meta-decision theory is a very ambitious and long-term research agenda, this dissertation focuses on a small-world[2] but real decision problem frequently confronted in evaluating public policies that are implemented for managing environment and resources.

Next, section 1.2 presents the well-established technique of decision trees (Raiffa 1968; Winterfeldt and Edwards 1986) and expounds meta-decision problems in terms of modeling decision behaviors under uncertain states of the world through the use of decision trees. Decision trees represent a collection of a set of possible actions that can be taken by the decision makers, the possible set of probable events that ensue as a result of decision makers' actions and lastly the possible set of outcomes. I am choosing the tool of decision trees because they are the underlying common structure in many otherwise disparate normative and descriptive decision theories. Section 1.3 presents the cognitive perspective of regulated vehicle owners through a decision tree, and describes the complex courses of actions, uncertain events/states of the world, and the outcomes in the context of specific regulatory mechanism being implemented in the Atlanta airshed. I also present a theoretical basis to designate cooperative and non-cooperative decision behaviors that emerge in Atlanta's regulatory mechanism. Section 1.4 briefly outlines the quasi-experimental research design and empirical methodology used to estimate cooperative and non-cooperative decision behaviors of high-emitting vehicle owners in Atlanta. This section also presents limitations of the study. Finally, section 1.5 lays the road map for each chapter of the dissertation.

---

[2] Joyce (1999) provides a formal definition to distinguish between grand-world and small-world decision problems, which is implied here. Informally, grand-world and small-world decision problems respectively entail infinite and finite space-time horizons in perceiving the outcomes of decision-makers' actions.

1.2: Decision trees and meta-decision problems in behavioral models

Von Neumann and Morgenstern (1944), Raiffa (1968), Brown et al (1974), Holloway (1979), and Winterfeldt and Edwards (1986) have developed the technique of decision trees to analyze the decisions under uncertainty and to suggest normative recommendations to the decision maker regarding what s/he should do in the face of a given decision problem. Decisions are uncertain because "the outcome of a decision often depends not only on the option chosen but also on the external events not under the decision maker's control (Winterfeldt and Edwards 1986: 63).

A generalized one-stage decision tree, as shown in figure 1.1, represents n possible actions branching out from top to bottom. Each action a_i entails e_{ij} events with a probability $P(e_{ij})$, such that $\sum_{j=1}^{mi} P(e_{ij}) = 1$. Each act a_i entailing event e_{ij} results in an outcome x_{ij}. It is assumed that the decision maker obeys axioms of rationality: completeness, transitivity, continuity and independence.[3] The most commonly employed *dominance* decision rule in RCT then states that the decision maker should choose the act that maximizes Expected Value (EV), which is defined as follows:

(1.1): EV (a_i) = $\sum_{j=1}^{mi} P(e_{ij}) x_{ij}$

In the case that we replace the scalar outcomes x_{ij} with a utility function $u(x_{ij})$, the *dominance* decision rule states that the decision-maker should choose the act that maximizes Expected Utility (EU),[4] which is defined as follows:

(1.2): EU (a_i) = $\sum_{j=1}^{mi} P(e_{ij}) u(x_{ij})$

A cut through a generalized multi-stage decision tree is shown in figure 1.2. The multi-stage tree has n initial acts, n_i events following act a_i, n_{ij} acts following event e_{ij}, and n_{ijk} final events f_{ijk}, followed by outcomes x_{ijkl}. The *dominance* decision rule is to maximize EV of act a_i, which is calculated as follows:

(1.3): EV (a_i) = $\sum_{j=1}^{ni} P(e_{ij}) max_k \{\sum_{l=1}^{nijk} P(f_{ijk}) x_{ijkl} \}$

---

[3] Completeness requires that a decision maker is able to establish a preference order for all the outcomes (i.e. either $x_i > x_j$ or $x_j > x_i$ or $x_i \sim x_j$). Transitivity requires that if decision maker prefers x_i over x_j and x_j over x_k then s/he should also prefer x_i over x_k. Continuity requires that if a decision maker has a preference order $x_i > x_j > x_k$ then there exists a unique p such that $p(x_i) + (1-p)x_k \sim x_j$. Independence requires that if a decision maker has a preference order $x_i > x_j$, then $p(x_i) + (1-p)x_k > p(x_i) + (1-p)x_k$ for all x_k and $p \in (0,1)$. Descriptive decision theorists have shown that human decision makers violate all the four axioms under some contextual conditions.
[4] Savage (1954) and Harsanyi (1967) proposed replacing EU with Subjective Expected Utility (SEU), which allows use of Bayesian probability theory to implement the dominance decision rule.

Decision Maker

ACT$_1$ ……   ACT$_i$ ……   ACT$_n$

E$_{11}$ E$_{1i}$ E$_{1m1}$ E$_{i1}$ E$_{ii}$ E$_{imi}$ E$_{n1}$ E$_{ni}$ E$_{nmn}$

x$_{11}$ x$_{1i}$ x$_{1m1}$ x$_{i1}$ x$_{ii}$ x$_{imi}$ x$_{n1}$ x$_{ni}$ x$_{nmn}$
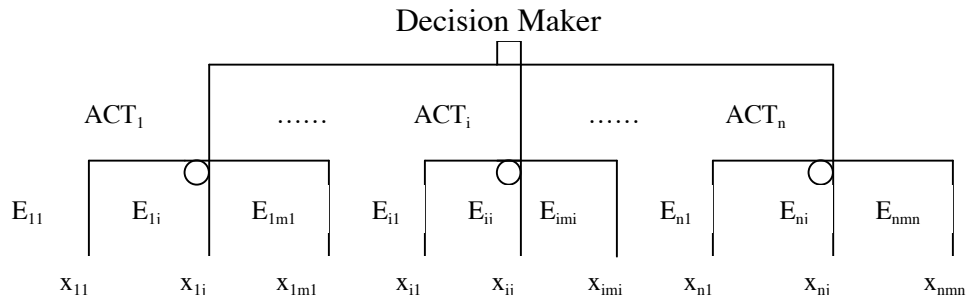
Figure 1.1: A generalized one-stage decision tree representing actions, events and outcomes (adapted from Von Winterfeldt and Edwards 1986: 75)

Decision Maker

ACT a$_1$ ……   ACT a$_i$ ……   ACT a$_n$

E$_{i1}$ E$_{ij}$ E$_{ini}$

ACT b$_{ij1}$ ACT b$_{iik}$ ACT b$_{ijnij}$

F$_{iik1}$ F$_{ijkl}$ F$_{ijknijk}$

OUTCOMES   x$_{iik1}$ x$_{iikl}$ x$_{iikniik}$
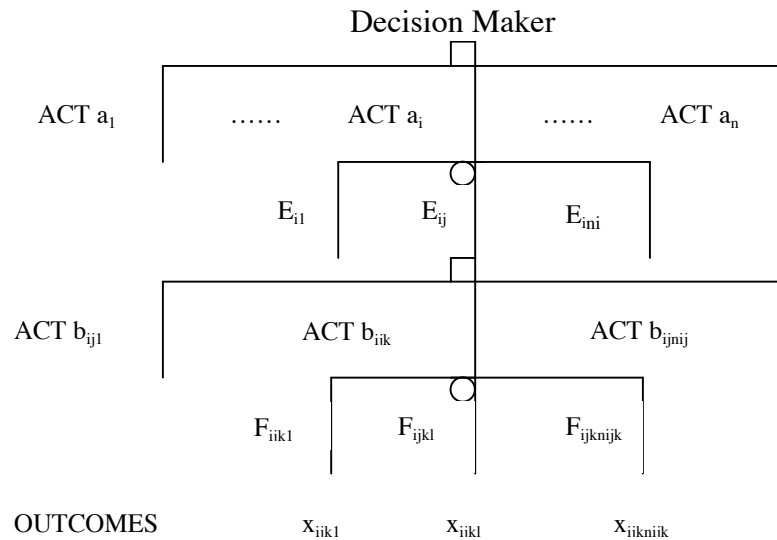
Figure 1.2: A cut through a generalized multi-stage decision tree representing actions, events and outcomes (adapted from Von Winterfeldt and Edwards 1986: 82)

The EU hypothesis for a generalized multi-stage decision tree correspondingly states that a rational decision agent should choose the act that maximizes EU of act a$_i$, which is calculated as follows.

(1.4): EU (a$_i$) = $\sum_{j=1}^{ni}$ P (e$_{ij}$) max$_k$ {$\sum_{l=1}^{nijk}$ P (f$_{ijk}$) u (x$_{ijkl}$) }

"Descriptive" decision theories challenge the EV and/or EU hypotheses. Simon (1977; 1982) dealt a serious blow to RCT by positing that decision makers do not obey the *dominance* decision rule (as shown in equations 1.1, 1.2, 1.3 and 1.4), rather they choose an action that *satisfies* their minimum thresholds for EV/EU for an action. Simon

7

called it a *satisficing* decision rule. Kahneman and Tversky (1979) dealt another serious blow to EV/EU hypotheses by positing that the cognitive faculties of individuals are not perfect enough to carry out complex computations before every real-world decision. They rather proposed *prospect* decision theory that has four important elements, each of which is derived from experimental evidence: First, decision makers employ an editing stage in which rules either dictate choices or transform gambles before they are evaluated. Second, decision makers choose a reference point (from which gains and losses are measured). Third, decision makers construct a riskless value function over gains and losses. Finally, decision makers construct a subjective function that weights probabilities nonlinearly and applies the resulting "decision weights" to outcomes to evaluate gambles/courses of actions. Zadeh (1965) devised the concept of *fuzzy set* theory, which has a logic that systematically differs from the underlying logic of RCT and EV/EU hypotheses. Fuzzy sets, for example, need not be transitive and completely known, while RCT requires its decision makers not only to know all the choices but also to be consistent in making their choices. It has been shown by numerous psychologists that the assumptions of transitivity and completeness do not describe human decision behavior. In a nutshell, from a descriptive perspective, Simon's satisficing theory, Kahneman and Tversky's prospect theory and Zadeh's fuzzy set theory have provided alternative decision theories that do not agree with the EV/EU hypotheses postulated in RCT. From a normative perspective, however, the EV/EU hypotheses still merit instrumental value as guideposts and reference points in providing methodological tools to elicit the values of decision makers (Keeney 1988; Keeney 1992; Keeney 1996; Keeney and Raiffa 1976).

In this dissertation, I use the tool of decision trees to illustrate that the EV hypothesis is neither provable nor disprovable from a meta-decision theoretical perspective because competing decision theories systematically differ in resolving meta-decision problems to operationalize the concept of decision trees. In equation 1.1, to take the simplest case, we come across three different kinds of variables: actions, events, and outcomes, which by assumption are known to the decision maker. Stronger versions of these equations (von Neumann and Morgenstern 1944) also require that the probabilities of events e_{ij} also be known to the decision makers. The meta-decision problems, which a decision maker confronts before or during the structuring process of a decision (tree), are of three broad types:

1) Which actions are included in the set of actionable actions (i.e. which cut-off criteria are used to terminate the search for more actionable actions)? And, which events and probabilities of those events are included in the set of events? Does the decision maker use Bayesian or Frequentist probabilities?

2) Which values are used to measure/quantify the set of outcomes? And, which weights are assigned to these values (the price mechanism being one way of assigning the weights)? In the language of economic theory, what should be the arguments as well as the functional specifications of the utility functions?

3) Which decision rule is used to make a choice (i.e. dominance, satisficing, fuzzy etc.)? More broadly, which decision theory (i.e. rational, satisficing, prospect, fuzzy etc.) should be used to structure and evaluate the decision tree?

Some of these meta-decision problems are age-old, going back to the times of Plato and Aristotle, and recurring since then in various forms and disciplines. Although each of these meta-decision problem merits a treatise in itself, I am not able to address all of them in this dissertation. My focus is rather on problem no. 2; however, problems 1 and 3 are also dealt with briefly in chapter 3. Next, section 1.3 presents a decision tree from the perspective of the regulated vehicle owners in the Atlanta airshed, and in the process expounds the meta-decision problems (especially no. 2) in the context of a real-world decision process. The real world decision process to be explored in detail in this dissertation is the case study of the vehicle owners' decision behaviors from 1997 to 2001 in response to the federally mandated public policy intervention of the vehicle inspection and maintenance program in the Atlanta airshed.

1.3 Cooperative and non-cooperative decision behaviors: a decision tree from the perspective of the regulated vehicle owners in Atlanta's regulatory mechanism

Pursued under the US Clean Air Act Amendments of 1990, motor-vehicle Inspection and Maintenance (IM) programs require periodic testing of on-road vehicles to diagnose whether the emission control system on a vehicle is working correctly, and if not, then the vehicle owner is required to repair it (EPA 1993; EPA 1994). Conceptually, the IM program is based on the precept of reducing CO, HC and NOx tail-pipe emissions from mobile on-road sources, especially by targeting high-emitting vehicles through the periodic inspection and efficient maintenance of emission control systems of on-road

vehicles. CO, HC and NOx emissions pose adverse risks to human health because they react in the atmosphere, especially during the high summer temperatures, to form atmospheric ozone, which has been found to be correlated with increased incidence of emergency visits for asthma-related respiratory attacks (Friedman, Powell et al. 2001). A brief history, rules and evaluation studies of the IM program in the Atlanta airshed is presented in chapter 4.

A recent US National Research Council report evaluating US IM programs states that "typically, less than 10% of the fleet contributes more than 50% of the emissions for any given pollutant…Thus, the largest potential reductions in emissions from IM programs are associated with a small number of high-emitting vehicles" (NRC 2001:5). Despite the lack of consensus and scientific uncertainty about the definition of high-emitters, previous studies (NRC 2001; Wenzel 1997) show that between 10% and 27% of vehicles that fail an IM test (based on EPA/state emission cut-points) never pass the test. Their exact fate has not been well characterized, although some have been found to be still in operation in IM areas more than a year after their last test (Harrington, McConnell et al. 2000; Stedman, Bishop et al. 1997; 1998). Next, I present a decision tree that shows (1) the actionable choices (2) probable events and (3) outcomes for each path of action and events faced by the high-emitting vehicle owners in the Atlanta airshed in response to the IM policy intervention.

Figure 1.3 depicts the structure of a two-stage decision tree from the perspective of the regulated vehicle owners in the Atlanta airshed.[5] The IM program in the Atlanta Airshed relies on the regulatory punishment strategy of denying the vehicle registration inside the 13 county program-area to vehicle owners whose vehicles do not pass the IM test. In game theoretical language, this regulatory punishment strategy sets up an incentive mechanism for the high-emitting vehicle owners, which is one possible mechanism out of many others to attain the valued outcome of reducing vehicular emissions. Given this incentive mechanism of regulatory punishment, it is the voluntary decision of high-emitting vehicle owners either to pursue a cooperative strategy and carry out actual repairs on the emission control systems of their vehicles or to pursue a non-cooperative strategy by circumventing the regulatory punishment mechanism and

---

[5] Though the decision game continues for failed vehicles beyond the stage 2, the addition of stage 3 really complicates the decision tree but does not change many of the outcomes. In other words, stage 2 may be taken as sum of all the stages occurring after the stage 2.
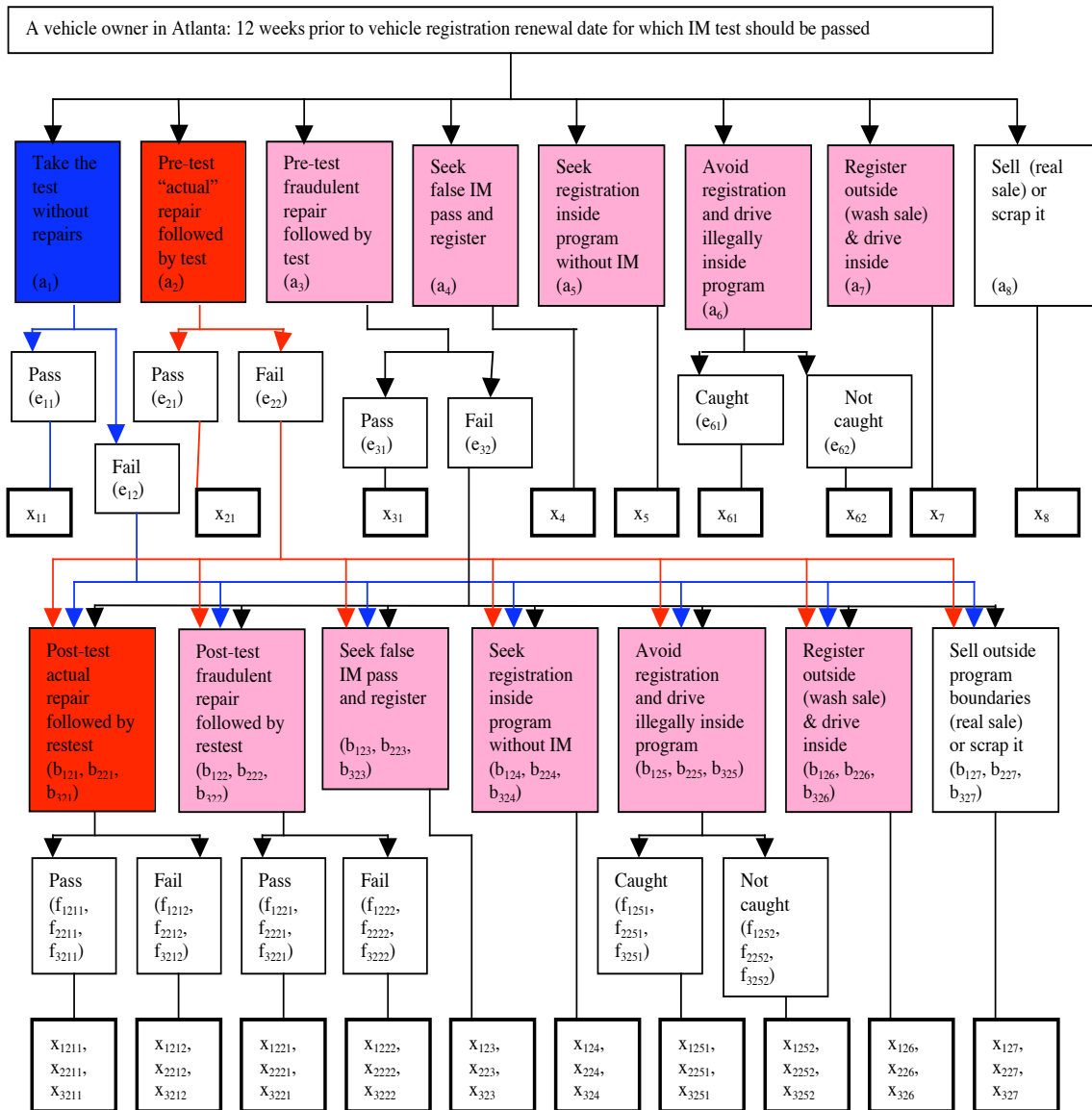
Figure 1.3: A decision tree showing sets of actions, events and outcomes faced by a vehicle owner in the Atlanta airshed due to the IM program regulations

pursuing one of the following non-cooperative strategies: pre-test or post-test fraudulent repairs, false IM passes through connivance with the management of the IM program testing stations, registering their vehicles inside the program boundaries without passing the IM test by bribing the vehicle registration authorities, avoiding the vehicle registration altogether, or more tactfully, by registering the vehicles outside the program

11

area through "wash sales"[6] or "pseudo addresses" and continuing to drive the vehicle inside the 13-county area. Vehicle owners also have the choice of scrapping or selling/replacing their vehicles and thus choosing to "exit" from the decision game.

Translating Figure 1.3 in tabular form, Table 1.1 lists all the possible 39 paths of actions and events leading to outcomes for the vehicle owners in the Atlanta airshed. By definition (i.e. given the emission cut points of the IM program), a normal-emitting vehicle owner will expect his/her vehicle to pass the emissions test without any repairs of emission control systems [i.e. a vehicle owner will expect Probability of the event e_{11} [P (e_{11})] to be close to 1 and $P(e_{12})$ to be close to 0]. Since the IM program is not designed to have any impact on the emission production of normal emitters, I designate this fleet of vehicles (or path no. 1) as the control group in quasi-experimental terminology. The possibility that a normal emitting vehicle fails the initial IM test (i.e. observed $P(e_{12}) = 1$) is also included in the decision tree.

The decision tree, as translated in table 1.1, becomes more interesting from the perspective of the high-emitting vehicle owners, who expect their vehicles to fail the emissions test without any repairs of emission control systems [i.e. $P(e_{11}) < P(e_{12})$]. RCT (as formally written in equation 1.3) will predict that high-emitting vehicle owners will choose an action that maximizes the expected value of their outcomes. As I have pointed out earlier, the crucial meta-decision question (much debated in RCT) concerns how vehicle owners will measure the outcomes. In table 1.1, I use a cost function to measure the outcome for each path (the idea being that the rational vehicle owner finds the maximum expected value in an act that minimizes the expected cost). It is however possible that those vehicle owners are also concerned with measuring the outcomes of their actions in terms of two additional criteria: pollution prevention (i.e. emission reduction) that will benefit the entire society, and fairness. If we measure the outcomes on the three dimensional criteria (costs, emissions and fairness), the optimal actions suggested by rational choice theory can be different than the case where outcomes are only measured in terms of one criterion (costs).

In my view, the hostile debate between economists (who insist on measuring outcomes only in terms of costs and benefits) and social psychologists/political scientists

---

[6] Through a "wash sale", a vehicle owner retains the use of the vehicle inside the IM program boundaries even after selling and/or re-registering it outside. This is contrasted with a "real sale", when a vehicle owner truly sells the vehicle outside the program boundaries to a new owner.

Table 1.1: Possible decision paths and their outcomes as function of costs for vehicle owners in response to IM program regulation in the Atlanta airshed

No.	Observed	Path	Nature of Path	Outcome	Outcome as function of costs
1	Yes	$a_1 \to c_{11}$	Control	x_{11}	$c_1 + c_2$
2	Yes	$a_1 \to c_{12} \to b_{121} \to f_{1211}$	Cooperative	x_{1211}	$c_1 + 2.c_2 + c_3 + c_9 + c_{10}$
3	Yes	$a_1 \to c_{12} \to b_{121} \to f_{1212}$	Non-cooperative	x_{1212}	$c_1 + 2.c_2 + c_3 + c_9 + c_{10} + c_{11}$
4	Yes	$a_1 \to c_{12} \to b_{122} \to f_{1221}$	Non-cooperative	x_{1221}	$c_1 + 2.c_2 + c_3 + c_4 + c_{10}$
5	Yes	$a_1 \to c_{12} \to b_{122} \to f_{1222}$	Non-cooperative	x_{1222}	$c_1 + 2.c_2 + c_3 + c_4 + c_6 + c_{11}$
6	Yes	$a_1 \to c_{12} \to b_{123}$	Non-cooperative	x_{123}	$c_1 + 2c_2 + c_5$
7	Yes	$a_1 \to c_{12} \to b_{124}$	Non-cooperative	x_{124}	$c_1 + c_2 + c_6$
8	No	$a_1 \to c_{12} \to b_{125} \to f_{1251}$	Non-cooperative	x_{1251}	$c_1 + c_2 + c_8$
9	No	$a_1 \to c_{12} \to b_{125} \to f_{1252}$	Non-cooperative	x_{1252}	$c_1 + c_2$
10	Yes*	$a_1 \to c_{12} \to b_{126}$	Non-cooperative	x_{126}	$c_1 + c_2 + c_7$
11	Yes	$a_1 \to c_{12} \to b_{127}$	Exit	x_{127}	$c_1 + c_2 + c_{12}$ (or c_{13})
12	Yes	$a_2 \to c_{21}$	Cooperative	x_{21}	$c_1 + c_2 + c_3 + c_9 + c_{10}$
13	Yes	$a_2 \to c_{22} \to b_{221} \to f_{2211}$	Cooperative	x_{2211}	$c_1 + 2.c_2 + 2.c_3 + 2.c_9 + c_{10}$
14	Yes	$a_2 \to c_{22} \to b_{221} \to f_{2212}$	Non-cooperative	x_{2212}	$c_1 + 2.c_2 + 2.c_3 + 2.c_9 + c_{10} + c_{11}$
15	Yes	$a_2 \to c_{22} \to b_{222} \to f_{2221}$	Non-cooperative	x_{2221}	$c_1 + 2.c_2 + c_3 + c_4 + c_9 + c_{10}$
16	Yes	$a_2 \to c_{22} \to b_{222} \to f_{2222}$	Non-cooperative	x_{2222}	$c_1 + 2.c_2 + c_3 + c_4 + c_9 + c_{10} + c_{11}$
17	Yes	$a_2 \to c_{22} \to b_{223}$	Non-cooperative	x_{223}	$c_1 + 2.c_2 + c_3 + c_5 + c_9$
18	Yes	$a_2 \to c_{22} \to b_{224}$	Non-cooperative	x_{224}	$c_1 + 2.c_2 + c_3 + c_6 + c_9$
19	No	$a_2 \to c_{22} \to b_{225} \to f_{2251}$	Non-cooperative	x_{2251}	$c_1 + c_2 + c_3 + c_8 + c_9$
20	No	$a_2 \to c_{22} \to b_{225} \to f_{2252}$	Non-cooperative	x_{2252}	$c_1 + c_2 + c_3 + c_9$
21	Yes*	$a_2 \to c_{22} \to b_{226}$	Non-cooperative	x_{226}	$c_1 + c_2 + c_3 + c_7 + c_9$
22	Yes	$a_2 \to c_{22} \to b_{227}$	Exit	x_{227}	$c_1 + c_2 + c_3 + c_9 + c_{12}$ (or c_{13})
23	Yes	$a_3 \to c_{31}$	Non-cooperative	x_{31}	$c_1 + c_2 + c_3 + c_4$
24	Yes	$a_3 \to c_{32} \to b_{321} \to f_{3211}$	Cooperative	x_{3211}	$c_1 + 2.c_2 + 2.c_3 + c_4 + c_9 + c_{10}$
25	Yes	$a_3 \to c_{32} \to b_{321} \to f_{3212}$	Non-cooperative	x_{3212}	$c_1 + 2.c_2 + 2.c_3 + c_4 + c_9 + c_{10} + c_{11}$
26	Yes	$a_3 \to c_{32} \to b_{322} \to f_{3221}$	Non-cooperative	x_{3221}	$c_1 + 2.c_2 + 2.c_3 + 2.c_4$
27	Yes	$a_3 \to c_{32} \to b_{322} \to f_{3222}$	Non-cooperative	x_{3222}	$c_1 + 2.c_2 + 2.c_3 + 2.c_4 + c_{11}$
28	Yes	$a_3 \to c_{32} \to b_{323}$	Non-cooperative	x_{323}	$c_1 + 2.c_2 + c_3 + c_4 + c_5$
29	Yes	$a_3 \to c_{32} \to b_{324}$	Non-cooperative	x_{324}	$c_1 + c_2 + c_3 + c_4 + c_6$
30	No	$a_3 \to c_{32} \to b_{325} \to f_{3251}$	Non-cooperative	x_{3251}	$c_1 + c_2 + c_3 + c_4 + c_8$
31	No	$a_3 \to c_{32} \to b_{325} \to f_{3252}$	Non-cooperative	x_{3252}	$c_1 + c_2 + c_3 + c_4$
32	Yes*	$a_3 \to c_{32} \to b_{326}$	Non-cooperative	x_{326}	$c_1 + c_2 + c_3 + c_4 + c_7$
33	Yes	$a_3 \to c_{32} \to b_{327}$	Exit	x_{327}	$c_1 + c_2 + c_3 + c_4 + c_{12}$ (or c_{13})
34	Yes	a_4	Non-cooperative	x_4	$c_2 + c_5$
35	Yes	a_5	Non-cooperative	x_5	c_6
36	No	$a_6 \to c_{61}$	Non-cooperative	x_{61}	c_8
37	No	$a_6 \to c_{62}$	Non-cooperative	x_{62}	0
38	Yes*	a_7	Non-cooperative	x_7	c_7
39	Yes	a_8	Exit	x_8	c_{12} or c_{13}

Where, c_1: testing fee = \$ 25, c_2: travel & queuing time for trip to IM station, c_3: travel & queuing time for trip to repair workshop, c_4: fraudulent repair cost, c_5: bribe to IM testing station for clean piping, c_6: bribe to vehicle registration authorities for registration without IM pass, c_7: cost of a fake address/holding a PO Box, c_8: cost of fine if caught driving without valid registration, c_9: actual repair cost, c_{10}: parts cost, c_{11}: cost/mental tension of keeping a lemon/IM failed vehicle, c_{12}: cost of traveling without an owned vehicle, c_{13}: cost differential between a new and old vehicle.

(who insist on measuring outcomes in terms of broader group-level social and political

values) can be dissolved if an agreement is reached at the meta-decision level between

the two regarding which criteria/values should be used to measure the outcomes. The rest of the dissertation is an attempt to make this meta-decisional point clearer. In the remaining section 1.3, I will show that RCT will predict domination of non-cooperative decision behaviors if the outcomes are only measured in terms of cost functions. I also discuss why is it equally important to measure the outcomes from the second and third dimensions of emission reductions and fairness respectively.[7]

Suppose that the high-emitting vehicle owner is extremely thoughtful and rational and duly considers each decision in depth.[8] S/he draws the decision tree of figure 1.3 (because it lists all the possible actions available to her/him as well as all possible events pursuant to those actions). By virtue of her expertise in economic theory, she can also write the cost functions. Suppose she thinks of following 13 kinds of costs, a combination of which can befall her in the event of one or the other action in the decision tree: c_1: testing fee = \$ 25, c_2: travel & queuing time for trip to IM station, c_3: travel & queuing time for a trip to repair workshop, c_4: fraudulent repair cost, c_5: bribe to IM testing station for clean piping, c_6: bribe to vehicle registration authorities for registration without IM pass, c_7: cost of a fake address/holding a PO Box, c_8: cost of fine if caught driving without valid registration, c_9: actual repair cost, c_{10}: parts cost, c_{11}: cost/mental tension of keeping a lemon/IM failed vehicle, c_{12}: cost of traveling without an owned vehicle, c_{13}: cost differential between a new and old vehicle. For analytical purposes, she further assumes that $c_1 < c_2 < c_3 < c_4 < c_5 < c_6 < c_7 < c_8 < c_9 < c_{10} < c_{11} < c_{12} < c_{13}$. An empirical investigation will be not much different from this ranking of costs; but the point is that the ranking of costs is a subjective preference ordering function if we consider Bayesian rational choice theory; and an objective preference ordering if we consider Frequentist rational choice theory.[9]

In the next step, the rational high emitter, who wants to minimize costs as an outcome of any action that she takes, will consider outcomes of any possible 38 paths (path nos. 2 to path no. 39) and decide her course of action. It will be useful to go through the heuristics of each path and show how each path is designated as cooperative or non-cooperative (or exit) before I prove that the expected value of non-

---

[7] The decision matrices with multi-criteria outcomes are discussed in this context in chapter 3.
[8] The possibility that the vehicle owner is non-rational is considered in detail in chapter 3.
[9] There are 2^{13} possible ranking orders of costs, which, fortunately, empirically are of much smaller magnitude because certain ranking orders can be ruled out due to fixed constraints.

cooperative actions will be higher than the cooperative actions if costs are the only dimension on which outcomes are measured and if the vehicle owner can establish a partial rank ordering of the expected costs.

In the first stage of the decision tree, the high emitting vehicle owner can decide to take any of the 8 courses of action: a_1: take the vehicle to emissions test without any repairs; a_2: carry out pre-test "actual" repairs and then test the vehicle; a_3: carry out pre-test "fraudulent" repairs and test the vehicle; a_4: seek a false IM pass by offering a side payment to IM testing station personnel; a_5: seek registration inside IM program boundaries without passing the IM test by offering a side-payment to the vehicle registration authorities at the county level; a_6: simply avoid registration of vehicle and keep on driving illegally inside the program boundaries; a_7: register the vehicle outside the program boundaries on a pseudo address (wash sale) but keep on driving the vehicle inside the program boundaries; a_8: exit the program by scrapping or selling the vehicle.

Given these available options, the thoughtful vehicle owner will consider the possible events that can follow any of her/his courses of action and measure the expected value of each action based on the outcomes (in terms of costs associated with that action). There are only two kinds of uncertain events that can happen to her/him if she takes the vehicle to the IM testing station (i.e. a_1 or a_2 or a_3): either she passes the test (e_{11}, e_{21}, or e_{31}) or she fails the test (e_{12}, e_{22}, or e_{32}). In the former case, her vehicle is emitting lower and in the latter case higher CO and HC emissions as compared to the emission cut-points established by GA-DNR for that particular model/make of vehicle.

If she fails the initial test, she enters the second stage of the decision game/tree; and then is again confronted with 7 courses of actions (b_{121},…,b_{127}; b_{221},…, b_{227}; b_{321},…,b_{327}). If she decides to take the vehicle for a second (or third, fourth…) test (i.e. b_{121}, b_{122}, b_{123}; b_{221}, b_{222}, b_{223}; b_{321}, b_{322}, b_{323}), she will again expect any of two events: either pass or fail the test. If she fails the second time, the loop of the second stage continues until her next birthday. In order to estimate the expected values of each course of action, it is very important that she has some subjective probability whether her car would pass the test after no repairs, actual repairs or fraudulent repairs. The probability of passing the test for a high-emitting vehicle owner increases if she either carries out actual or fraudulent repairs. Actual repairs are supposedly more durable and compliant with the laws, but they entail higher repair/parts costs. On the other hand, fraudulent repairs are not as

15

durable (but durable enough for her to pass the test) and not compliant with the laws, but they entail relatively lower repair/parts costs (hence her ranking, $c_4 < c_9$). Now I assert that if she measures the outcomes only on the one scale of minimizing costs for herself, she should prefer to carry out a_3 in the first stage of the game and not a_2 (same applies if she's in second or higher stage). More specifically, the outcome x_{31} will entail lower costs as compared to the outcome x_{21}. Path no. 23 in table 1.1 shows that her cost function will be $(c_1 + c_2 + c_3 + c_4)$ if she arrives at an outcome of x_{31} (i.e. she passes the initial test after fraudulent repairs). Similarly, path no. 12 in table 1.1 shows that her cost function will be $(c_1 + c_2 + c_3 + c_9 + c_{10})$ if she arrives at an outcome of x_{21} (i.e. she passes the initial test after actual repairs). Now if she just compares action a_2 with a_3 and feels that the probability of passing the test would be higher than the probability of failing test after either actual or fraudulent repairs, the dominance decision rule (equation 1.1) suggests that she should prefer alternative a_3 over the alternative a_2 because a_3 has higher expected value. This can be seen algebraically by showing that $[(c_1 + c_2 + c_3 + c_4) < (c_1 + c_2 + c_3 + c_9 + c_{10})] \Rightarrow [(c_4) < (c_9 + c_{10})]$, which is an empirical fact any vehicle technician will readily tell you (i.e the cost of fraudulent repairs is less than the cost of the actual repairs). The logic of the expected value hypothesis (assuming that the decision maker only considers cost as the sole argument of her outcome function) therefore recommends that the rational vehicle owner carry out fraudulent repairs and pursue a non-cooperative/non-compliant strategy and defy the spirit of CAAA 1990, damage the environment through vehicular pollution and take a free ride on clean air. My argument (from a meta-decisional perspective) is that it is not just the expected value hypothesis but also the assumptions built into it that result in such paradoxical recommendations for rational agents/fools. In this case, the assumption is that the outcomes are measurable and all the values of the decision maker can be concatenated into costs (and benefits concomitantly).

Next, consider if the decision maker compares the alternatives a_4 to a_7 with her non-dominated alternative a_3, she finds that some of them may even entail lesser costs and dominate the alternative a_3, and they definitely dominate the alternative a_2. Note that alternatives a_4 to a_7 are all non-cooperative strategies/actions. Either she can bribe the IM testing station personnel (action a_4) or she can bribe the vehicle registration authorities (action a_5); however, in both cases she will have to find testing station/vehicle registration authorities that are willing to accept her bribe offer. In case her search cost

as well as the accepted bribe amount (c_5 or c_6) is less than the actual repair cost (c_9 and c_{10}), the non-cooperative alternatives a_4 and a_5 will dominate the cooperative alternative a_2. If she compares a_3 with a_4 and a_5, the alternative a_3 will dominate both a_5 and a_6 if $c_4 < c_5$ and if $c_4 < c_6$. However, in case $c_5 < c_4$ and/or $c_6 < c_4$, then the alternatives a_4 and a_5 will dominate a_3. In game theoretical language, this points to the existence of multiple Nash equilibria in this decision game.

Similar arguments can be made about the alternative a_6. If the probability of being caught driving without valid registration is low [$P(e_{61}) < P(e_{62})$] as well as the fine after being caught c_8 is lower than the actual repair cost (c_9 and c_{10}), the action a_6 (non-cooperative) will dominate the action a_2 (the cooperative alternative). Similarly a_7 will dominate a_2 if the cost of registering the vehicle outside the program area (c_7) is lower than the actual repair cost (c_2). Outcomes for all the 39 paths of the decision tree in figure 1.3 are shown in cost functional form in table 1.1. The table also shows which path is designated as control, cooperative, non-cooperative or exit.

Now suppose we designate a cooperative action (shown in red color in figure 1.3) as A_c and a non-cooperative action (shown in pink color in figure 1.3) as A_{nc}, and further suppose that cost minimization is the only criterion of the high-emitting vehicle owner given the regulatory incentive mechanism ($c_1 < c_2 < c_3 < c_4 < c_5 < c_6 < c_7 < c_8 < c_9 < c_{10} < c_{11} < c_{12} < c_{13}$), then EV ($A_{nc}$) > EV ($A_c$). In a nutshell, this proves that the expected value of the non-cooperative actions dominate the cooperative actions given the existing cost-structure imposed by the regulatory mechanism of IM policy intervention in the Atlanta airshed. A rational vehicle owner should decide to pursue a non-cooperative action and not pursue a cooperative action, if cost minimization were her only value to measure the outcomes of her actions and if the cost structure has the following incentive mechanism: ($c_1 < c_2 < c_3 < c_4 < c_5 < c_6 < c_7 < c_8 < c_9 < c_{10} < c_{11} < c_{12} < c_{13}$). In case, the vehicle owner is not rational and acts as a satisficing, prospective or fuzzy decision maker, the expected value of each alternative will be different than the case of rational choice EV hypothesis, which I discuss in chapter 3. The more complicated problem is the hypothesis presented by political science and social psychology theory: decision makers act rationally, but they do not measure their outcomes only on a cost-benefit basis; rather, other values, such as being good law-abiding citizens, long-term environmental preservation and fairness, can also play a pivotal role in their *non-linear* calculus of choosing the appropriate courses of actions. The prediction of political science theory

will be different; and it will expect high-emitting vehicle owners to be more cooperative because they want to be good law-abiding citizens and they value prevention of air pollution more than the actual repair costs. From a meta-theoretical perspective, the question how many high-emitting vehicle owners actually pursue cooperative strategies and how many others pursue non-cooperative strategies, becomes an important empirical research issue for deciding which theory more accurately describes and predicts the human decision behavior in regulatory mechanism environments. Suppose, X_{ijkl} represents the total number of players who pursue any of the 39 decision paths resulting in outcomes x_{ijkl}, as shown in figure 1.3 and described in table 1.1, then the probability of cooperative decision players in the quasi-experimental treatment group can be theoretically calculated by equation 1.5, which is essentially the total number of cooperative players divided by the total number of both cooperative and non-cooperative players in the decision game:

(1.5): Pr [Cooperation] = [X_{1211} + X_{21} + X_{2211} + X_{3211}]/[X_{1211} + X_{21}+ X_{2211} + X_{3211} + X_{1212} + X_{1221} + X_{1222} + X_{123} + X_{124} + X_{1251} + X_{1252} + X_{126} + X_{2212} + X_{2221} + X_{2222} + X_{223} + X_{224} + X_{2251} + X_{2252} + X_{226} + X_{31} + X_{3212} + X_{3222} + X_{323} + X_{324} + X_{3251} + X_{3252} + X_{326} + X_4 + X_5 + X_{61} + X_{62} + X_7]

The EV hypothesis will be justified if we find a yes as an answer to the following question: Do all the high emitting vehicle owners act rationally in the face of the given regulatory incentive mechanism by not cooperating with the IM program rules [i.e. Pr [Cooperation] = 0]? There is not a straight answer to this question, because non-cooperative vehicle owners do not confess in public that they are not cooperative. Given the perverse incentive structures of high-emitting vehicle owners, it is not possible for the mechanism designers to have complete information for empirically estimating the values of all X_{ijkl} in equation 1.5. Further, if we do not find all the high-emitting vehicle owners to be non-cooperative, it is possible that their underlying decision processes are bounded-rational or fuzzy; or perhaps they act more as good citizens than indifferent consumers. Yet, rational choice theory predicts that all of them should be non-cooperative if cost minimization is their only value.

The first hypothesis [H_1] that is tested in this study states that the probability of cooperation by high-emitting vehicle owners is 0% in the Atlanta Airshed. If all the high-emitting vehicle owners do not cooperate with the rules of the vehicle Inspection and Maintenance (IM) program implemented under the clean air act amendments of 1990,

then the EV hypothesis predictions will appear to hold. On the other hand, if all the high-emitters appear to be cooperative, then the EV hypothesis will be disconfirmed while the predictions of political science/social psychology theory will hold. Finally, if there is evidence of some high-emitting vehicle owners who cooperate with the IM program rules and some others who do not cooperate, it will partially confirm the predictions of both game theory and social psychology theory, and partially disconfirm them. I do not expect to have perfect cooperation nor perfect non-cooperation, and rather expect that the results will confirm the findings of the previous controlled experimental studies under voluntary mechanisms (Ledyard 1995).

Previous evaluation studies of the IM program in the Atlanta airshed in particular and in the USA in general have found that IM program is not as effective as it is expected to be. These evaluation studies increasingly use remote sensing data to ascertain the IM program effectiveness with respect to the on-road vehicular fleets. These studies compare from a very broad and aggregated perspective the *total* effects of IM program intervention.[10] In this dissertation, I am interested in dissecting the total effects to measure the IM program effectiveness, and focus on how cooperative and non-cooperative decision behaviors of high-emitting vehicle owners decrease or increase the effectiveness of IM programs. In other words, I explore the question: what is the impact on vehicular tail-pipe emissions of the cooperative and non-cooperative decision behaviors of high-emitting vehicle owners? The mechanism designers/regulators are interested in knowing the outcomes of vehicle owners' decision behaviors not only from the perspective of their cost functions, but also the emission outputs. All x_{ijkl} in figure 1.1/table 1.3 should not be just treated as scalar quantities, rather they are vectors, as in multi-criteria outcome games (Keeney and Raiffa 1976; Yu 1979; Yu 1985).

The dissertation tests a second hypothesis [H_2] that is of special environmental decision-making interest in the ongoing debate about the effectiveness of environmental regulations, such as IM programs, in reducing the on-road vehicular emissions. The null hypothesis states: The difference between the vehicular emissions of cooperative and non-cooperative vehicle owners is not significantly different than zero. The alternative hypothesis states this expectation: Vehicles belonging to the non-cooperative fleets emit

---

[10] These studies are reviewed in chapter 4.

significantly more vehicular tail-pipe emissions than the vehicles of cooperative fleets. This expectation is based on the assumption that cooperative vehicle owners have carried out repairs on their emission control systems according to IM program rules, while the non-cooperative vehicle owners do not carry out the repairs and try to avoid the IM program or circumvent its regulatory punishment strategy, as shown in figure 1.3.

Mechanism designers can also consider an estimation of fairness effects due to the policy intervention of the IM program and resulting decision behaviors of high-emitting vehicle owners. In other words, it can be asked: how are the costs of the IM program distributed across the socio-economic contexts of the vehicle owners in the Atlanta airshed? This question is also important from the cognitive perspective of the vehicle owners and adds a third argument to the estimation of outcome sets in figure 1.3/table 1.1. A third null hypothesis [H_3] tested in the dissertation states: The odds are equal that high-emitting vehicle owners live in the same income-level neighborhoods as do the normal emitters. The alternative hypothesis states: the odds are higher that high-emitting vehicle owners live in lower-income-level neighborhoods than do the normal emitters. The third hypothesis is tested to determine the fairness effects of the IM program policy intervention.

A fourth null hypothesis [H_4] tested in the dissertation states: The odds are equal that cooperative high-emitting vehicle owners live in the same income level neighborhoods as do the non-cooperative high-emitting vehicle owners. The alternative hypothesis states: The odds are higher that cooperative high-emitting vehicle owners live in relatively higher-income-level neighborhoods than do the non-cooperative high-emitting vehicle owners. The fourth hypothesis tests the contextual conditions of cooperative and non-cooperative high-emitting vehicle owners. Hypotheses about the racial and demographic composition of normal emitters vs. high-emitters and cooperative vs. non-cooperative high-emitters are also tested. Next, section 1.4 briefly describes the quasi-experimental research design that is used to test the hypotheses listed above.

1.4: The quasi-experimental research design and limitations of the study

The research methodology is designed in three phases. Phase I empirically addresses the following question: (1) what is the probability of a high-emitting vehicle owner deciding to cooperate under the rules of the IM program in the Atlanta airshed? And how does the probability of cooperation change over time from 1997 to 2001?

Phase II, the core of this research design, seeks an empirical answer to the following question: (2) what is the impact on vehicular emissions of CO, HC and NOx due to the cooperative and non-cooperative decision behaviors of high-emitting vehicle owners in the Atlanta airshed? Finally, phase III is designed to empirically answer the following question (3) what is the effect of socio-economic contextual conditions on the probability of a high-emitter pursuing a cooperative or non-cooperative action? The socio-economic contextual conditions include median household income, per capita income and racial profile of the vehicle owners at the ecological level of census block group in which their vehicles are registered.

I used Continuous Atlanta Fleet Evaluation (CAFE) on-road vehicle emissions remote sensing (RS) data (1997-2001) collected by AQL, IM program and exemption data (1997-2001) provided by the Georgia Department of Natural Resources (GA-DNR), Vehicle Registration data (1997-2002) provided by the Georgia Department of Motor Vehicles and Safety (GA-DMVS), census data (2000) released by the United States census bureau and climate data (1997-2001) released by the National Climatic Data Center. The descriptive statistics of the relevant variables are presented in table 5.1 and discussed in detail in chapter 5. Next I briefly outline the quasi-experimental research design for each of the three phases, which is explained in further detail in chapter 5.

1.4.1: Phase I: Estimating cooperative and non-cooperative behavioral strategies of high-emitters

Phase I of this research design empirically explores the following question: (1) what is the probability of a high-emitting driver cooperating or not cooperating under the rules of the IM program in the Atlanta airshed? The mechanism designers cannot have all the information needed to ascertain precisely how many high-emitting vehicle owners pursued cooperative and non-cooperative actions. Previous researchers have employed the methodology of collecting the data about vehicle owners through randomly testing the vehicles by road-side pullovers; but this methodology has proven to be overwhelmingly cost-ineffective and time-consuming. The IM data cannot capture all the non-cooperative strategies listed in Figure 1.3. Fortunately, AQL in Atlanta regions has been collecting remote sensing data since 1994[11] and trying to capture observations of

---

[11] This study however uses remote sensing data from 1997 onwards because the IM and vehicle registration data between 1994 and 1996 have been found to be less reliable.

about 1% of the total on-road fleet annually in the Atlanta airshed.[12] The remote sensing data cannot provide 100% information about each of the cooperative and non-cooperative paths listed in table 1.4 and figure 1.3. Despite some limitations discussed later in this section, as well as in chapter 5, the available remote sensing data lets us track most of the cooperative and non-cooperative actions of high-emitters in the annualized samples. Next I explain how I measured (the measurable) cooperative and non-cooperative behavioral strategies by using the remote sensing data from 1997 to 2001.

As shown in figure 1.4, the remote sensing sample of on-road data containing observations on vehicles found registered in the state of Georgia is subdivided into two further fleets. The IM eligible fleet contains vehicles that were required under the rules of the IM program to appear in IM test and the IM ineligible fleet contains vehicles that were not required under the rules of the IM program to appear in IM test. The eligibility criteria reflect the rules of IM program for each evaluation year, such as gasoline powered cars and light duty trucks under GVWR 8000 lbs between 3 to 25 year ages having odd model years were required to be tested in 1999 and even model years in 2000.[13] The eligible fleet contains vehicles of two further kinds: IM exempted vehicles that are checked by tracking the eligible fleet vehicles in the exemption data, and vehicles that were not exempted from IM test. The non-exempted eligible fleet of vehicles of the on-road sample is tracked in the IM program data using the variables VIN and model year. The vehicles found in the IM program data are further sub-divided into three fleets: control fleet if the vehicle passed the initial IM test, retest-pass fleet if the vehicle failed the initial test but passed the re-test, and retest-fail fleet if the vehicle failed the initial test and again failed the re-test or did not re-appear in the IM test.

The eligible fleet vehicles not found in the IM data of the evaluation year contain vehicles of three further kinds: first, vehicles that were found in previous IM cycle and failed an initial test. These vehicles belong to the "missing failed" fleet as they are found registered inside IM program boundaries without passing the IM test in the year of evaluation but they have failed the initial test in the previous IM cycle. Second, similarly, the missing IM-eligible vehicles that passed the initial test in the previous IM cycle are

---

[12] Chapter 5 presents more details about sampling sites and times of remote sensing data.
[13] Detailed IM program rules can be found at http://www.cleanairforce.com/ and at EPA's website http://www.epa.gov/oms/epg/progeval.htm. Some major rules are also discussed in chapter 4.
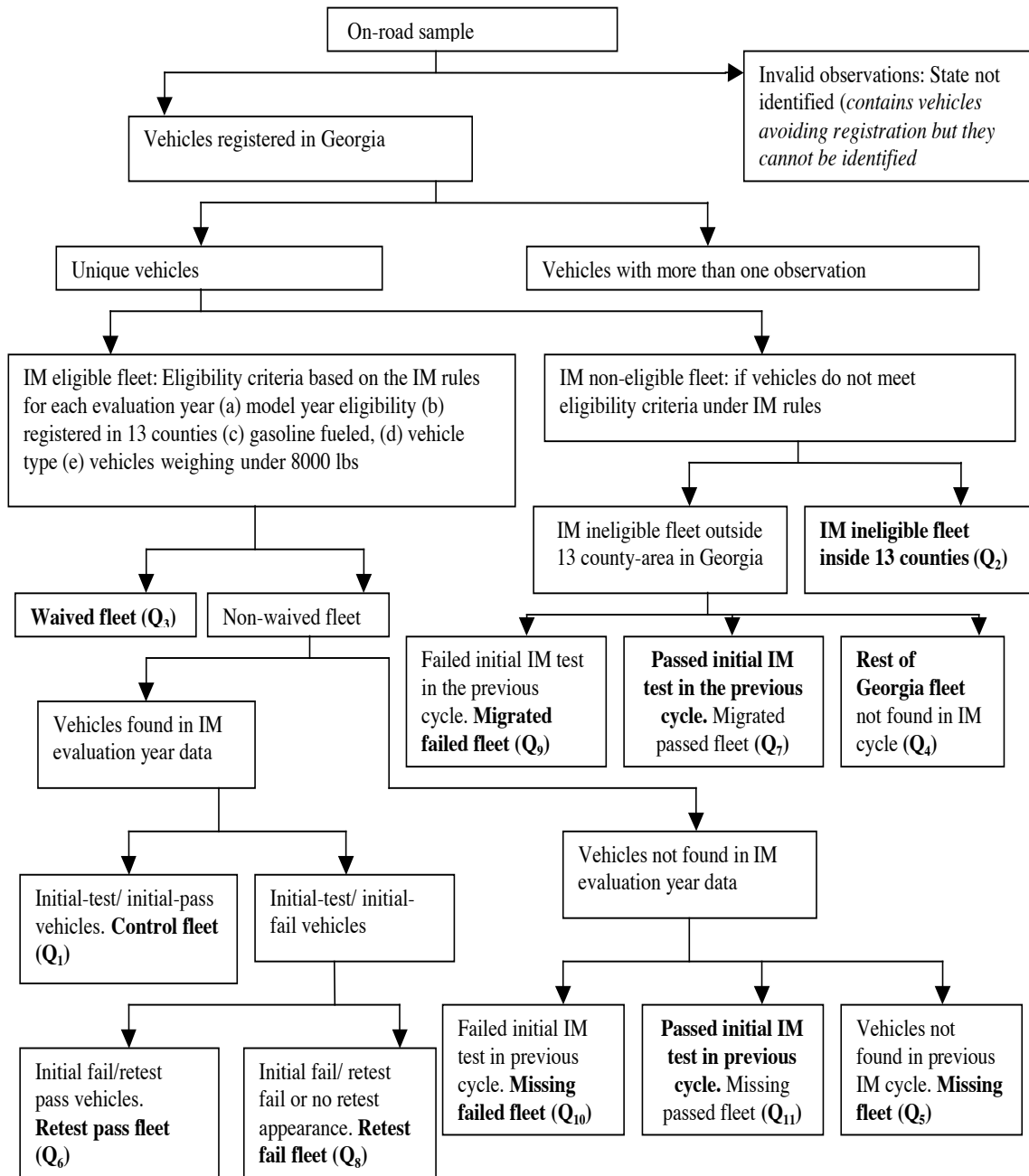
Figure 1.4: The sampling methodology for characterizing 11 vehicle fleets (shown in bold font) by using the on-road emissions data

classified as belonging to the "missing passed" fleet. Third, the IM eligible missing vehicles that were not found in either current or previous IM cycle are categorized as the missing fleet. These missing fleet vehicles potentially indicate the error rate in VIN and

model year variables as well as reporting error in IM, registration and remote sensing databases.

From the set of unique valid vehicles that were designated as non-eligible vehicles, two further sub-fleets are defined. The first sub-fleet includes vehicles that are registered inside the 13 county-area but are not eligible to appear in the IM test as per IM program rules. This fleet is designated as the IM ineligible fleet inside the 13 county-area for that particular evaluation year. It is a noteworthy fact that under the biennial IM testing program, the ineligible fleet contains vehicles that underwent testing in the previous year. The second sub-fleet includes vehicles that are registered in the state of Georgia outside the 13 county IM program boundaries.

The rest of Georgia fleet outside the 13 county-area is further subdivided into three fleets. First, the "migrated failed" fleet includes vehicles that are found to have failed an initial IM test in the previous IM cycle. This category of vehicles represents those high emitting vehicles that appear to have migrated outside the IM boundaries but are still driven inside the IM boundaries. Second, the "migrated passed" fleet includes vehicles that are found to have passed an initial IM test in the previous IM cycle. Third, the "rest of the Georgia" fleet which includes vehicles that have no record in the previous IM cycle.

In a nutshell, as the bold-faced terminal nodes in figure 1.4 show, the sample of the on-road data that is selected to evaluate the IM program for a given year is subdivided into 11 vehicle fleets: control [Q_1], IM ineligible inside 13 county area [Q_2], waived [Q_3], rest of the Georgia fleet [Q_4], missing [Q_5], retest-pass [Q_6], migrated-passed [Q_7], retest-fail [Q_8], migrated-failed [Q_9], missing-failed [Q_{10}], and missing-passed [Q_{11}]. These eleven fleet types are coded as eleven binary variables ($\sum_{q=1}^{11} Q_q$), such as the variable "retest pass" [Q_6] is valued 1 if the vehicle belongs to the retest pass fleet and 0 otherwise and the variable "retest-fail" [Q_8] is valued 1 if the vehicle belongs to retest-fail fleet and 0 otherwise, and so on. The control group (initial test/initial pass) vehicles [Q_1] serve as the reference fleet in regression models. *Vehicles belonging to retest pass and migrated passed fleets are characterized as belonging to cooperative vehicle owners, while vehicles belonging to retest fail, missing fail, migrated failed and missing passed fleets are characterized as belonging to non-cooperative vehicle owners.*

Assuming that a vehicle is characterized as a high-emitter after it fails the initial IM test as per IM emission cut-point rules, then the probability of cooperation is

measured by taking a ratio of the cooperative fleet vehicles (belonging to the retest pass and migrated passed fleets in this analysis) to the total initial fail vehicles (belonging to the retest pass, migrated passed, retest fail, migrated failed, missing failed and missing passed fleets in this analysis). Conversely, the probability of non-cooperation is equal to 100% minus the probability of cooperation. Formally:

(1.6): Pr [Cooperation] = [Q_6 + Q_7]/[Q_6 + Q_7 + Q_8 + Q_9 + Q_{10} + Q_{11}]

The empirical methodology to estimate probability of cooperation, as described in equation 1.6, has the following limitations:[14] (1) The probability of cooperation is over-estimated because one cannot find those vehicle owners that simply avoid registration of their vehicles inside the state of Georgia and still drive them inside the IM program boundaries without valid license plates. Further, the probability of cooperation is also over-estimated because the methodology cannot single out those vehicle owners who register their vehicles out of Georgia state (through a wash sale) and still drive inside the program area (i.e. path nos. 10, 21, 32 and 38 in table 1.1 are only partially captured). (2) The probability of cooperation is under-estimated because the methodology cannot separate the high-emitting vehicle owners who do pre-test actual repairs and pass the initial test (path 12 in table 1.1) from the normal emitting vehicle owners who pass their initial test without any actual repairs (path 1 in table 1.1). (3) Both IM and remote sensing data methodologies contain the possibility of a matching error due to the incorrectly reported VIN and model year variables. This matching error is probably represented in the category of "missing fleet" vehicles. A detail comparison between equation 1.5 and equation 1.6 is presented in chapter 5 with a discussion of the methodological biases that arise due to incomplete information, which is the most important limitation of this research design.

 Phase II: Estimating the emission reduction impact of cooperative and non-cooperative behavioral strategies of high-emitters

Phase II of the research design explores the following empirical question: What is the impact on the outcomes of vehicular emissions due to the cooperative and non-cooperative decision behaviors of high-emitting vehicle owners in the Atlanta airshed?

---

[14] Table 6.1 presents estimated probability of cooperation as described in equation 1.6. The results of Table 6.1 are discussed extensively in chapter 6. The expected biases and limitations of the results are also discussed in chapter 5.

Previous literature (NRC 2001) suggests that vehicular emissions (CO, HCs and NOx) are complex functions of three broad groups of parameters.

First, vehicular characteristics, including their technological specifications, affect the emissions. The vehicular characteristics include vehicle age, vehicle type, model, make, manufacturer, manufacturing country, and mileage of the vehicle. The technological parameters indicate if a vehicle is fitted with Air Injection Reactor system (AIR), Oxidation (two-way) catalyst (OXY), Three Way Catalyst (TWC), Exhaust Gas Recirculation (EGR), Closed Loop Combustion Control (CLL) and Thermostatic Air Cleaner (TAC). Vehicular and technological parameters ($\sum_{r=1}^{31} R_r$) are treated as control variables in the quasi-experimental research design. Chapter 4 explains their expected effects as proposed by theory.

Second, physical and temporal parameters at the time of measurement of vehicular emissions also affect the vehicular emissions. Physical parameters include speed and acceleration of the vehicle at the time of measurement, road grade at the remote sensing observation site, ambient temperature, atmospheric pressure and relative humidity. Physical ($\sum_{s=1}^{7} S_s$) and temporal ($\sum_{t=1}^{4} T_t$) parameters are also treated as control variables.

Third, vehicular emissions are also affected by the individual decision behaviors and broader policy parameters applicable in a specific place. I use 11 binary decision variables to depict the 11 kinds of vehicle owners, as shown in figure 1.4. The control group is represented by (normal emitting) vehicle owners in the remote sensing samples who passed their initial IM test. The control group also serves as a reference group in the statistical models. Two cooperative and four non-cooperative vehicular groups act as quasi-experimental treatment groups. Four additional groups of vehicles – the IM ineligible group from inside program, the rest-of-Georgia group from outside program, and the IM-waived group and the missing group – are included in the analysis because they are also observed on-road by the remote sensors. The 11 decision variables are depicted by ($\sum_{q=1}^{11} Q_q$).

Multiple statistical decision theory models, employing mixed-pooled time series multivariate generalized linear and non-linear regressions are used to test hypotheses concerning the impacts on vehicular emissions outcomes due to the cooperative and non-cooperative decision behaviors of high-emitting vehicle owners, after controlling for

technological, vehicular, physical and temporal parameters. Three (linear) equations are initially estimated to quantify/generalize the impact of cooperative and non-cooperative decision behaviors on the vehicular tail-pipe emissions[15]:

$(1.7): Y_{CO} = \alpha_0 + \sum_{q=2}^{11} \beta_q Q_q + \sum_{r=1}^{29} \gamma_r R_r + \sum_{s=1}^{7} \phi_s S_s + \sum_{t=2}^{5} \delta_t T_t + \sum_{t=2}^{5} \sum_{q=2}^{11} \Delta_{tq} T_t Q_q + \varepsilon_1,$

$(1.8): Y_{HC} = \alpha_0 + \sum_{q=2}^{11} \beta_q Q_q + \sum_{r=1}^{29} \gamma_r R_r + \sum_{s=1}^{7} \phi_s S_s + \sum_{t=2}^{5} \delta_t T_t + \sum_{t=2}^{5} \sum_{q=2}^{11} \Delta_{tq} T_t Q_q + \varepsilon_1,$

$(1.9): Y_{NO} = \alpha_0 + \sum_{q=2}^{11} \beta_q Q_q + \sum_{r=1}^{29} \gamma_r R_r + \sum_{s=1}^{7} \phi_s S_s + \sum_{t=4}^{5} \delta_t T_t + \sum_{t=4}^{5} \sum_{q=2}^{11} \Delta_{tq} T_t Q_q + \varepsilon_1,$

Y_{CO}, Y_{HC} and Y_{NO} are measured in grams per gallon. Interaction effects [Δ_{tq}] are estimated in equations 1.7, 1.8 and 1.9 to test the changes in CO, HC and NO emission factors of 11 fleet types from year to year. The error terms ε_1, ε_2 and ε_3 are heteroskedastically robust errors. Furthermore, non-linear Box-Cox regression models are also estimated and the results from non-linear models are used to further specify transformed linear models (such as log-linear models). The details of these statistical models are presented in chapter 5. The results from these models are used to test the hypothesis whether cooperative decision behaviors, controlling for other variables, reduce vehicular emissions; and if they do reduce them, then by how much.

Phase III: Estimating the socio-economic contextual conditions of cooperative and non-cooperative vehicle owners

The contextual conditions of cooperative and non-cooperative vehicle owners occur at two ecological levels. At the individual level, the socio-economic parameters of vehicle owners, such as their individual income level and their race, can hypothetically affect their individual behaviors. Due to privacy issues, it is not possible to access data that provide information about the individual level socio-economic parameters of vehicle owners. This is another major limitation of this study.[16] A second kind of individual

---

[15] Tables 6.2, 6.3 and 6.4, which are discussed in detail in chapter 6, present respectively the estimated equations 1.7, 1.8 and 1.9.

[16] Individual-level information is treated as missing or incomplete for the purposes of this study because it is practically not possible to empirically collect this information for the entire sample during the study period. Income tax data at the household level is protected under the rights of individual privacy. Property tax data of the households can be used to elicit property tax value of a house, which in turn can be used as a proxy variable to reflect the income of the vehicle owners in the study sample. The use of property tax value as a proxy income variable will however raise many other indefensible issues, such as the difference between renters and house-owners, business cycle trends in the housing market, and above all, the non-linear relationship between the property value and income of the vehicle owners. Another option was to elicit a survey response from the vehicle owners in the study sample and directly and indirectly ask these drivers questions about their income and other conventional contextual conditions. The survey was expected to have the serious problem of response bias. Second, the sample of the study

parameters include information about the vehicle characteristics as well as their technological specifications, represented by variables ($\sum_{r=1}^{31} R_r$), which are included as controlling variables in phase III of the research design.

The group level contextual variables include socio-economic and demographic parameters of the vehicle owners' neighborhoods. The 2000 Census data provides information about group level parameters at multiple ecological levels (block group, tract, county etc.). I use two ecological levels to characterize the socio-economic conditions. First, census block group level is primarily chosen because it is the smallest ecological level at which socio-economic data about the neighborhoods of vehicle owners' addresses is publicly available; and it is recommended that smallest ecological level data should be chosen to explore the contextual conditions of decision makers (Boyd and Iversen 1979). Second, county level is chosen because most of the public policy decisions are operationalized at the level of county governments, such as vehicle registrations and law enforcements.

The group level socio-economic and demographic contextual conditions that are hypothesized to affect the decision behaviors of high-emitting vehicle owners include the following variables (measured at the level of census block-groups): (1) economic variables: the median household income [W_1], the per capita income [W_2], the median home value [W_3], % employed [W_4]; (2) social variables: percentage of white population [W_5], percentage of black population [W_6], percentage of Hispanic population [W_7], percentage of Asian population [W_8], percentage of other races' population (such as native Americans, pacific Americans) [W_9]; (3) demographic variables: percentage of male population [W_{10}], percentage of female population [W_{11}], percentage of population between the ages of 18 and 24 years [W_{12}], percentage of population between the ages of 25 and 34 years [W_{13}], percentage of population between the ages of 35 and 44 years [W_{14}], percentage of population between the ages of 45 and 54 years [W_{15}], percentage of population between the ages of 55 and 65 years [W_{16}], and percentage of population aging 65 years and above [W_{17}].

The contextual conditions of decision makers (i.e.11 fleet types) are ascertained through two kinds of models: first, linear ecological regression is employed to test the

could have been drastically reduced from thousands to a few hundred. Third, the study period could have been reduced from 5 years (1997 to 2001) to just the current year (2003). Furthermore, an additional survey would have involved huge monetary and time costs.

differences in the median household income of vehicle owners' blockgroups as per 11 fleet types, while controlling for other vehicular parameters as well as social, demographic and economic variables. The following ecological regression equation is estimated:

(1.10): $W_1 = \alpha_0 + \sum_{q=1}^{10} \beta_q Q_q + \sum_{r=1}^{29} \gamma_r R_r + \sum_{w=2}^{15} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t + \varepsilon_1$

Secondly, a multinomial variable "fleet type" [F] is created, which is coded 0 for control group, 1 for IM ineligible group, 2 for waived fleet, 3 for rest of Georgia fleet, 4 for missing fleet, 5 for retest pass fleet, 6 for migrated pass fleet, 7 for retest fail fleet, 8 for migrated fail fleet, 9 for missing fail and 10 for missing pass fleet. In order to test the hypotheses about the social, economic and demographic contextual conditions of different groups of decision-makers/vehicle owners that affect the probability of a vehicle owner being in one of the 10 groups relative to the control group, the following multinomial logistic regression equation is estimated.

(1.11): $Pr(F=i)/Pr(F=0) = \{e \,^{**}[\sum_{r=1}^{29} \gamma_r R_r + \sum_{w=1}^{15} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t]\}$, where $i=1,2,\ldots10$.

A major limitation of the multinomial logistic model concerns the problem of the "ecological fallacy" [Robinson (1950), Riley (1964), Alker (1969) and Stokes (1969)] because census data variables reflect the group-level contextual conditions of decision behaviors. Arguably, the qausi-experimentalist will commit the ecological fallacy if individual behaviors are *inferred* from group level variables[17].

Some researchers, such as Boyd and Iversen (1979) and King (1997), argue that one will commit the ecological fallacy if one attempts to derive inferences about the individual behavior from the group level variables; but they also emphasize the flip side that it will be fallacious if one ignores the group level contextual variables as explanatory parameters of individual decision behaviors. Boyd and Iversen's (1979) research emphasizes that *both* individual and group level contextual parameters should be included in the statistical decision models. King's (1997) research places emphasis on calculating the upper and lower bounds of socio-economic parameters for drawing ecological inferences about the individual decision behaviors by using the aggregate

---

[17] Due to the ecological fallacy issue, the following hypothesis is not testable in equation 1.12: The probability of cooperative behavior increases as *household income of the vehicle owner* increases, controlling for other independent variables. Rather the following hypothesis is tested in the study: The probability of cooperative behavior increases as *median household income of the census block group of vehicle owner's address* increases, controlling for other independent variables.

group-level data. I estimate equation 1.11 with both the individual-level contextual variables that can be feasibly collected as well as the socio-economic and demographic parameters of the vehicle owners observed in the census data at the block-group level. The upper and lower bounds of group level parameters (ν_c) estimated by multinomial logistic regression model of equation 1.12 represent "between-group" and not "within-group" variation, which is another major limitation of the study.

1.5 Dissertation outline

Chapter 2 presents a detailed discussion of the cooperative and non-cooperative decision behaviors under different contextual conditions. Contexts of voluntary and regulatory mechanism designs are explored in greater depth. The concept of adaptive environmental policy mechanism designs is also presented in chapter 2.

Chapter 3 presents research on the state of the expected value hypothesis in descriptive and normative decision theories, especially when outcomes are measured in multiple value dimensions. The concept of meta-decision models is also formally introduced in chapter 3.

Chapter 4 focuses on describing the regulatory mechanism of IM programs in the USA in general and Atlanta in particular. Secondly, prior empirical research on evaluating the effectiveness of IM programs in terms of reducing vehicular tail-pipe emissions is presented in chapter 4. Thirdly, various behavioral research studies that have been conducted to evaluate the decision behaviors of high-emitting vehicle owners are also presented in chapter 4.

Chapter 5 presents the research design and its limitations in greater detail. This chapter is also divided into three major sections, corresponding to the three major phases of the research design, and builds on the information provided in section 1.4. The first phase of research design discusses the methodology to measure cooperative and non-cooperative decision behaviors; the discrepancy between theoretical and empirical models is bridged. The second phase of the research design estimates the outcomes of cooperative and non-cooperative decision behaviors in terms of expected vehicular emissions. The third phase of the research design explains how hypotheses about the outcomes on the dimension of fairness are operationalized. This phase explores the methodology to test systematic differences about the socio-economic contextual conditions between normal and high-emitting vehicle owners, on the one hand, and cooperative and non-cooperative vehicle owners on the other hand. In

addition, the threats to internal, construct, statistical and external validities of the quasi-experimental research design as well as its limitations are presented in chapter 5.

Chapter 6 presents results for each phase of the research design. Chapter 7 contains a discussion on the analysis and implications of the results. In particular, the focus is on substantive environmental policy implications, decision theoretical implications and methodological implications.

COOPERATIVE AND NON-COOPERATIVE DECISION BEHAVIORS UNDER DIFFERENT CONTEXTUAL CONDITIONS: VOLUNTARY, REGULATORY AND ADAPTIVE ENVIRONMENTAL POLICY MECHANISMS

2.1: The Meta-decision problem of designing environmental policy mechanisms

Decision behaviors affect the environmental outcomes. Conversely, different contextual conditions, including our environments, affect the nature of social decisions. The interactive relationship between decision behaviors, on the one hand, and contextual conditions, on the other hand, thus remains an active area of research in social sciences, especially policy and decision sciences.

Enhanced understanding about the relationship between decision behaviors and contextual conditions provides important information both for evaluating current public policies and designing new policies. From the perspective of environmental policy, for example, it is an important question: do people, especially polluters, *decide* to cooperate with the community-mandated environmental laws? Furthermore, are there specific contextual conditions that affect people's decision behaviors that in turn affect environments? An answer to these questions would enable environmental policy makers to improve the design of policy mechanisms that protect environments because policy designs can be adapted to create contextual conditions that promote desirable decision behaviors.

In the previous experimental and non-experimental literature, decision behaviors have been studied under different kinds of contextual conditions and policy mechanisms. A very general framework of an experimental policy mechanism design was introduced by Mount and Reiter (1974), which I briefly present in section 2.2. Given this generic framework, it is possible to identify the following three broad kinds of environmental

policy mechanisms that share one common assumption: the outcomes accruing from decision makers' actions can be represented by a single commensurate[18] value.

(1) *Voluntary* policy mechanisms imply no governmental/policy intervention to preserve environmental values and resources. (2) *Regulatory* policy mechanisms imply "command and control" type of policy interventions to preserve environmental values and resources. (3) *Market-based* policy mechanisms imply tax- and subsidy-based policy interventions to control environmental resources in *real* markets and creation of emissions' permit trading in *artificial* markets. I present voluntary and regulatory mechanisms respectively in sections 2.2.1 and 2.2.2. Cooperative and non-cooperative decision behaviors that have been studied under the contextual conditions of voluntary and regulatory policy mechanisms are reviewed respectively in sections 2.3.1 and 2.3.2.

Since I focus in this dissertation on evaluating the decision behaviors under voluntary and regulatory mechanisms, I do not present a detailed review of market mechanisms. There are two kinds of market policy mechanisms: the first kind treats pollution as external effects of the "real" market processes and argues that policy interventions in the real markets should change the production level of externalities. Lindahl's (1919/1958) equilibrium theory is a standard example of modeling a real market mechanism in the case of external pollution effects, the updated details of which can be found in Baumol and Oates (1988) and Mas-Colell et al. (1995).[19] A second kind aims to create "artificial" markets for pollution permits. Clarke (1971), Groves (1973) and Groves and Ledyard (1977) are among the earliest examples of these kinds of market mechanisms, while Franciosi et al. (1993), Cason and Plott (1996) and Ben-David et al. (1999) provide examples of considerable recent research in this area. While artificial market mechanisms have been experimentally introduced in the case of "stationary" sources of pollution, such as SO_2 controls on industrial plants, it remains to be seen how they can be designed to control emissions/pollution for "mobile" sources of pollution, such as ozone-forming pollutants from high-emitting vehicle-owners. This is an active

---

[18] Expected value/expected utility representation of each element of the set of values (by which outcomes are measured in equation 1.1) assumes all the values are commensurable in units of monetary value or utility value. Mathematically, outcomes can be quantified for commensurate values through single-criteria maximization models under constraints. However, when the assumption of commensurability is relaxed, the multiple-criteria decision-making models (MCDM) come into play, which I present in chapter 3.

[19] Recent introduction of congestion taxes in London is an example of "real" market mechanisms to improve air quality as well as reduce congestion.

area of research in environmental policy (Xepapadeas 1997), but beyond the scope of this dissertation.

In section 2.4, I introduce the notion of *adaptive* environmental policy mechanisms, which are designed at two levels. At the level of action, the policy designer *descriptively* evaluates whether citizens respond cooperatively or non-cooperatively with the prevalent (voluntary, regulatory and market) environmental policy mechanisms. At the level of reflection, the meta-decision problem of designing an appropriate environmental policy mechanism is *normatively* considered by the researcher in the light of decision behaviors and environmental outcomes that emerge at the level of action and decisions and outcomes that are desirable at the end of policy horizon. The level of action is descriptive, while the level of reflection is normative. Adaptive policy mechanisms prescribe socio-scientific learning-based policy interventions that are iteratively adjusted according to changing contextual conditions for attaining the desirable outcomes, which balance pluralistic values.[20]

One important meta-decision problem concerns the question: can we compare regulatory mechanisms with voluntary, market or adaptive mechanisms? Though this is an extremely important question from the perspective of meta-decision theory as well as policy analysis and evaluation, it remains beyond the scope of empirical scrutiny in this dissertation. However, since the data analysis results show that a regulatory mechanism is not producing the best outcomes in terms of cost-effective emission reductions and fairness values in the Atlanta airshed, it is natural to assume that there exist alternative mechanisms which may produce better environmental outcomes than the outcomes of the present regulatory mechanism. In this context and in the light of the empirical results, alternative mechanisms –voluntary, market and adaptive-- are briefly discussed in chapter 7 of the dissertation.

2.2: Environmental policy mechanism designs and decision behavioral models

The main components of experimental mechanism designs are *environments*, *outcomes*, *performance/value criteria*, *institutions* and *models of behavior* (Ledyard

---

[20] Adaptive policy mechanisms relax the assumption of commensurate value measurement, and allow the possibility of non-commensurate values on which decision makers do/should measure the outcomes of their actions. The case of multiple values that may include non-commensurate values is presented in chapter 3.

1995; Mount and Reiter 1974). Figure 2.1 presents structural components of a generic experimental mechanism design.
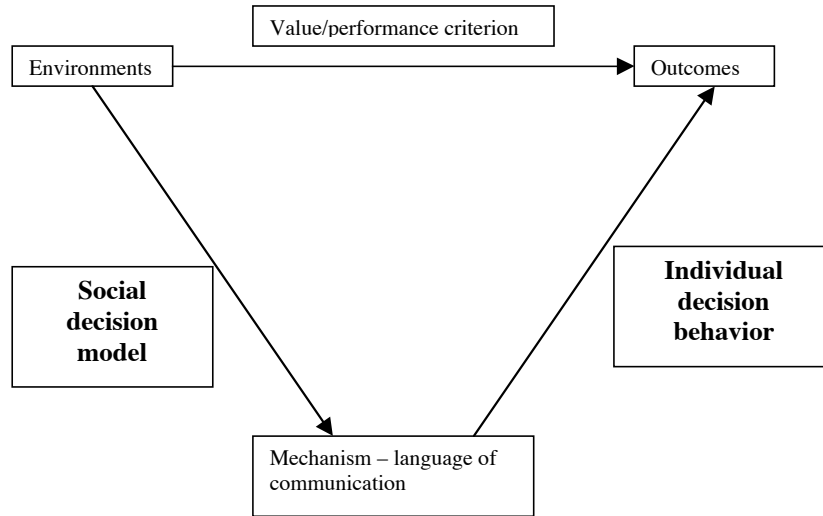
Figure 2.1: A generic environmental policy mechanism design (adapted from Mount and Reiter 1974)

Formally, in a very general sense, Ξ is a set of environments[21] and X is a set of outcomes.[22] $\Omega: \Xi \rightarrow X$ is the performance/value criterion[23] where $\Omega(e) = \{x\}$ is a function

---

[21] An *Environment* describes "the details of the situation that the analyst takes as given and the experimentalist manipulates: the exogenous variables. The environment includes the number of agents/people, their preferences and endowments, the physical constraints on their behavior (biological and physical laws), those aspects of the legal structure (such as property rights) that are taken as fixed, the structure of information (who knows what, and to what extent that might be common knowledge), the technical details and possibilities for production of goods and bads. Environment also includes a description of the range of possible outcomes of interest to agents/people/citizens." (Ledyard 1995:116)

[22] An *Outcome* describes "the final distribution of resources and payoffs. How each individual feels about the outcome depends on the particular environment since an individual's preferences for outcomes are part of the description of an environment." (Ledyard 1995:116)

[23] The *performance/value criterion* "determines (for each environment) a ranking over outcomes. The idea is that in each environment the best outcome is the one which is ranked highest by the performance/value criterion. A standard performance/value criterion used in experimental work is a cost/benefit decision rule, which computes the sum of payoffs received as a percent of the maximum attainable. From the perspective of the mechanism designer, only agents have detailed

which identifies the "best" outcomes for each environment e. The institution[24] is (Γ, g) where Γ is the language of mechanism, and $g\ (x^1,..., x^i,....,x^N)$ specifies the best outcomes which are chosen if each individual i responds to the institution with x^i. The behavioral model is μ where $\mu\ (e, (\Gamma, g)) = (x^1,..., x^i,....,x^N)$ specifies how each individual will actually respond if the environment is e and the institution is (Γ, g).[25]

Ledyard (1995: 117) notes: "To evaluate how well an institution performs (according to a particular performance criterion) we need to be able to predict what outcomes will occur in each environment when that institution is used. To do that we need a *model of behavior*; that is, we need a theory of how individuals respond in each environment to requests for information and action by an institution. From a very broad and general perspective, the behavioral model will predict different responses in different environments to the same institution as well as different responses in the same environment to different institutions."

Formally, the question is which policy mechanism actually results in the "best" outcomes for citizens of a society. This question, however, again leads us back to my original meta-decisional question: which values should be used to measure the outcomes and how should these values be weighed to determine what is the "best" outcome? The theory of policy mechanism designs is silent on this meta-decisional issue because it has taken for granted the measurement of the outcomes on the basis of cost-

---

and decentralized information about the range of outcomes and values used to measure those outcomes. The information is private property." (Ledyard 1995:116)

[24] The *Institutions* "arise to aggregate information and coordinate activities. An institution specifies who should communicate with whom and how, as well as who should take various actions and when." (Ledyard 1995:116) Each mechanism (voluntary, regulatory or market) results in different institutional arrangements and outcomes for the society and the individuals living in that social system.

[25] I define Γ_v as a voluntary mechanism, Γ_r as a regulatory mechanism, Γ_m as a market mechanism and Γ_a as an adaptive mechanism. Correspondingly μ_v, μ_r, μ_m and μ_a respectively denote behavioral models under voluntary, regulatory, market and adaptive mechanisms.

benefit decision rule[26], as also suggested by Ledyard (1995: 116).[27] Next, I show how voluntary and regulatory mechanisms differ from each other in terms of their specific environments, outcomes, performance/value criteria, institutions and models of behavior, while assuming that outcomes are rank ordered on the value/performance criterion of (a measurable) cost-benefit decision rule.

2.2.1: voluntary policy mechanisms

A voluntary mechanism (Γ_v) has been traditionally modeled as prisoner's dilemma game to model the problem of provision of public goods/environmental resources in a society (Hardin 1982; Ostrom 1990). Under a strict voluntary mechanism, the central governmental authority has at best minimal presence and acts primarily to coordinate the actions of citizens and protect property rights in public goods. The voluntary mechanism generates a behavioral model (μ_v) that is explained by a prisoners' dilemma model, which I explain below through a generalizable example in the language of decision trees and EV/EU hypothesis that was introduced in section 1.2.

Suppose Mary is asked to contribute \$ 200 (denoted as x_c^1) toward repairing the emission control systems on her high-emitting vehicle. Once the vehicle is repaired, the benefit of less vehicular emissions/better air quality will be shared by everyone in a society of 100,000 (or N) citizens. The same suggestion is made to 9,999 (or K) of Mary's neighbors/other citizens who also own high-emitting vehicles. Let's suppose further that there are 90,000 (or N-K) other vehicle owners in this society whose vehicles are clean/normal emitting. The individual benefit of Mary's contribution, let's suppose, is \$ 10 (or x_b^1), which is the value of clean air for Mary. Her individually rational strategy, as decided by EV/EU hypothesis (as well as cost-benefit decision rule), is to decline to

---

[26] The Net Present Value (NPV) rule of the cost-benefit decision algorithm states that the policy designer should maximize the present value of all beneficial outcomes minus costlier outcomes, subject to specified constraints (Prest and Turvey, 1965). Expressed mathematically:

Maximize: NPV = $\sum_{t=0}^{n} [(x_{bt} - x_{ct})/(1+r)^t]$. s.t. k is statisfied, $\forall$ k $\in$ {K}

where: NPV = net present value, x_{bt} = beneficial outcomes at time t, x_{ct} = costlier outcomes at time t, r = discount rate, n = planning horizon, k = particular constraints, {K} = complete constraint set. The decision rule is to choose the project or policy that has the largest NPV subject to the set of constraints.

[27] The case of multiple non-commensurably valued outcomes is considered in detail in chapter 3 both from the perspectives of descriptive and normative decision theories.

contribute because 10 < 200 (or $x_b^1 < x_c^1$). But if she does contribute, then not just her but all other citizens in the society also receive a return from her contribution. Suppose they also receive an average of $10 benefit in value due to the clean air from Mary's contribution. Then her $200 contribution would produce a $ 1,000,000 benefit (or x_B) for the entire society. Nevertheless, according to RCT, her dominant behavioral action is to withhold her contribution.

As Schmidz (1991: 62) puts it, voluntary mechanism examples, like Mary's choice example, "illustrates the general truth that contributing a unit of public good generates benefits for the group in excess of the unit's cost, but the unit's cost exceeds the benefits for the individual who contributes the unit. Each individual in the group is strictly better off withholding than contributing. Because the players of this 'game' decide as individuals rather than as a group, individually rational strategies thwart collective efforts to produce public goods. The incentive structure is that of Prisoner's Dilemma."

The "extensive"[28] decision tree form of incentive structure for a generalized prisoners' dilemma game, as explained in the preceding example, is presented in figure 2.2. Figure 2.2 uses the following notation:

x_c^1 = the unit investment that Mary/decision maker has to contribute if she cooperates.

x_c^K = the unit investment that K^{th} high-emitting vehicle owner has to contribute if she cooperates.

x_b^1 = the benefit to Mary/decision maker from her contribution of x_c^1.

x_b^K = the benefit to K^{th} high-emitting vehicle owner from her contribution of x_c^1.

x_B = Group benefit $\sum_i x_b^i$ in a group of N members with K polluters, where i = {1,2,.....N} and K ≤ N.

The outcomes matrix in figure 2.2 represents twelve *extreme* outcomes. The top row shows Mary's outcomes, the Kth row shows outcomes for Kth high-emitter (who faces a similar decision tree as Mary does) and the Nth row shows outcomes for N^{th}

---

[28] The "normal" form of a similar example can be seen at Schmidtz (1991:65).

Mary

Cooperate (A_c)   Not cooperate (A_{nc})

All others   …   No one   All others   …   No one
cooperate   cooperates   cooperate   cooperates

$(x_B - x_c^1)$ … $(x_b^1 - x_c^1)$ $(x_B - x_b^1)$ … (0) Outcomes for
Mary

…   …   …   …
…   …   …   …
…   …   …   …

$(x_B - x_c^K)$ … (x_b^1) $(x_B - x_b^1 - x_c^K)$ … (0) Outcomes for
K^{th} High emitter

…   …   …   …
…   …   …   …
…   …   …   …

(x_B) … (x_b^1) $(x_B - x_b^1)$ … (0) Outcomes for
N^{th} normal
emitter

Figure 2.2: A generalized decision tree representing the prisoners' dilemma game for provision of environmental goods under voluntary policy mechanisms

normal-emitter (who is affected by the decision behaviors of K high emitters in the society). Each column of outcomes' matrix in figure 2.2 represents four *extreme* scenarios:[29] (1) Mary cooperates and every other high-emitter cooperates; (2) Mary cooperates and no other high-emitter cooperates; (3) Mary does not cooperate and all other high-emitters cooperate; and (4) Mary does not cooperate and no other high-emitter cooperates. Because there is non-rivalry in the consumption of clean air/environmental resource, x_b is added to every citizen's benefit for each investment of x_c. Thus, if each high-emitter in the group of K high-emitters contributes (as in the first column of the outcome matrix in figure 2.2), each player's net gain will be the total benefit x_B, minus her own contribution of x_c, or $x_B - x_c$. The return to the entire society as a whole, formulated in terms of total benefits, x_B, is the sum of individual benefits gained by each individual member of the society. If one player withholds and the remaining

---

[29] The complete outcomes matrix for the group of 100,000 citizens would have 100,000 columns and 100,000 rows!

players cooperate (as in the third column of outcome matrix in figure 2.2), then the cooperative return is lowered by x_b, i.e. from x_B to $(x_B - x_b)$, because one less player is investing x_c. Each high-emitter's net gain will be $(x_B - x_b - x_c)$, except for the withholding high-emitter/Mary, whose net gain will be $(x_B - x_b)$, because she saves x_c by not contributing her share to clean the air.

Two more crucial assumptions are needed to be sure that the incentive structure of the public goods game presented in figure 2.2 is a prisoner's dilemma: for all citizens, (1) x_B substantially exceeds x_c,[30] and (2) x_c exceeds x_b. Schmidz says, "The first assumption assures that producing the good is important. The second assumption ensures that the incentive to withhold will be real. Together, the assumptions that x_B exceeds x_c and that x_c exceeds x_b are necessary and sufficient to ensure that the generalized collective action problem depicted in figure 2.2 is a Prisoner's Dilemma, exhibiting both the free rider and assurance problems" (Schmidz 1991: 65).[31] Further he explains that "in the Prisoner's Dilemma, players have a dominant strategy, and following it leads to wholesale withholding, which has the paradoxically self-defeating effect of *minimizing* the benefits players secure as a group" (Schmidz 1991: 65).

From a meta-decision theoretical perspective, the above-mentioned description of the provision of public goods as Prisoner's Dilemma contains not just two assumptions (i.e. $x_B >>> x_c > x_b$), rather it contains many other hidden assumptions that I have listed as meta-decision problems in sections 1.2 and 3.1. I will focus on the meta-decision assumption that citizens measure outcomes as single-valued monetized costs and benefits. I suspect that this grand assumption is one of the causes that we do not observe as many free-riders in actual public goods games as predicted by RCT/game theory. First, benefits of public goods cannot always be easily monetized. How can you

---

[30] If x_B does not exceed x_c for a player (such as $x_c > x_B > x_b$), then that player in the decision game is not cognitively playing a prisoner's dilemma game. In the case of IM program, for example, a high-emitting vehicle owner may value social benefit of reducing vehicular emissions to be less than repair costs. Note that even if a player is not cognitively playing in a prisoner's dilemma game, the non-cooperative action will still dominate her choices (if outcomes are measured on the value of cost-minimization), which in turn would have prisoner's dilemma model effects on the entire society, if and only if $(x_B >>> x_c > x_b)$ is true.

[31] It is on the basis of these two assumptions (i.e. $x_B >>> x_c > x_b$) that the incentive structure presented in figure 2.2 leads to the inference for Mary that EV $(A_{nc}) >$ EV (A_c), no matter what others play. The non-cooperative action thus dominates the cooperative action and Nash equilibrium is the fourth column in the outcome matrix of figure 2.2.

place a monetary value on one thousand tons of CO, HC and NOx? Some costs are probably easy to monetize, but the costs occurring in distant futures and/or intangible costs are not easily monetized due to the unresolved issues associated with finding agreeable discount rates (Costanza, d'Arge et al. 1997; Freeman 1993; Norton and Toman 1997). Second, the provision of public goods does not always have to be measured on the value of efficiency (which is the cornerstone of cost-benefit decision rule), rather the value of (both intra-generational and inter-generational) fairness also hypothetically plays a significant role in the provision of public goods, especially environmental resources such as clean air and biodiversity (Norton 1996; Norton 1997).

Figure 2.2 is a classical example of voluntary mechanism designs. Most of the experimental studies that have been conducted in the laboratory to investigate the provision of public goods assume an incentive structure that is very similar to figure 2.2. I review some of these studies in section 2.3.1. These experimental studies test the game theoretical prediction that decision makers should play non-cooperative/non-contribution strategies given the incentive structure, which is essentially similar to figure 2.2. Both real-world and controlled experimental studies show that people do cooperate/contribute higher-level provision of public goods than predicted by the game theoretical model presented in figure 2.2. Why is there a discrepancy between the game theoretical prediction and real-world practice? In my view, the answer to this question lies in digging out the pluralistic values of citizens in which they measure the outcomes of their actions. The game theoretical model depicts citizens as very narrow and myopic who are also able to reduce all of their values in terms of single-valued monetary costs and benefits. The reality is however much more complex and pluralistic.

Voluntary mechanisms existed in Atlanta before the introduction of IM policy intervention (i.e. before 1981). I have however no independent data that goes back to the early 1980s to show how voluntary mechanisms affected the air quality of the Atlanta airshed. In this dissertation, the focus is more on modeling the decision behaviors of vehicle owners after the regulatory mechanism was intensified/extended under the enhanced IM program, which began in January 1997.

In most of the experimental economics literature, cooperative and non-cooperative decision behaviors have been investigated under the framework of a

41

voluntary mechanism (Γ_v), which is briefly reviewed in section 2.3.1. In the case study of the Atlanta airshed, we cannot precisely say that IM program intervention entails a voluntary mechanism. Rather it is a case of regulatory mechanism, *even though* voluntary decision choice of cooperating or not cooperating with the mandatory regulation still remains a volitional choice with the vehicle owners. The incentive structure generated by a regulatory mechanism is presented in the next section.

2.2.2: regulatory policy mechanisms

Since the RCT theory predicts that every rational person should free ride under voluntary mechanisms, regulatory mechanisms were widely introduced in USA and Europe during the early 1970s to ensure the mandatory provision of environmental resources. Most of the regulatory mechanisms are designed to ensure that polluters do not emit above certain threshold values of pollutant emissions. In the case of vehicular emissions, these threshold values have been gradually reduced significantly over the last 30 years. I have two important points to make about the regulatory mechanisms. First, most of the regulatory mechanisms are single-valued programs, i.e. pollution reduction is their foremost important value. Most of these mechanisms assume the "polluter pays principle" (PPP), which in some cases have raised serious environmental justice concerns. Second, most of the regulatory mechanisms rely on introducing "regulatory punishment costs" (x_p) for those polluters who emit above the regulatory standards. The institution of regulatory punishments changes the incentive structure for individual decision-makers/polluters (as shown in figure 2.3) as compared to the voluntary mechanisms (as shown in figure 2.2) but regulatory incentive structures do not always ensure that polluters cooperate with the society to produce the desirable level of environmental goods.

Figure 2.3 presents a simplified incentive structure for Mary after the IM program regulation is introduced in the voluntary mechanism design of figure 2.2. Figure 2.3 uses the same notation as figure 2.2, except that x_p is added to represent the regulatory punishment for a non-cooperative high-emitting vehicle owner. In the case of the IM program, x_p means that the vehicle owner is not allowed to register his/her vehicle inside the program boundaries if his/her vehicle emits higher emissions than the regulatory standards and she fails the emissions test.

Now, if $x_p > x_c$, then outcomes in column 1 of figure 2.3 [$(x_B - x_c^1 - x_p^1)$, $(x_B - x_c^K - x_p^K)$] would reflect the Nash equilibrium and everybody will cooperate/contribute. On the

Mary

Cooperate (A$_c$)   Not cooperate (A$_{nc}$)

All others cooperate   …   No one cooperates   All others cooperate   …   No one cooperates

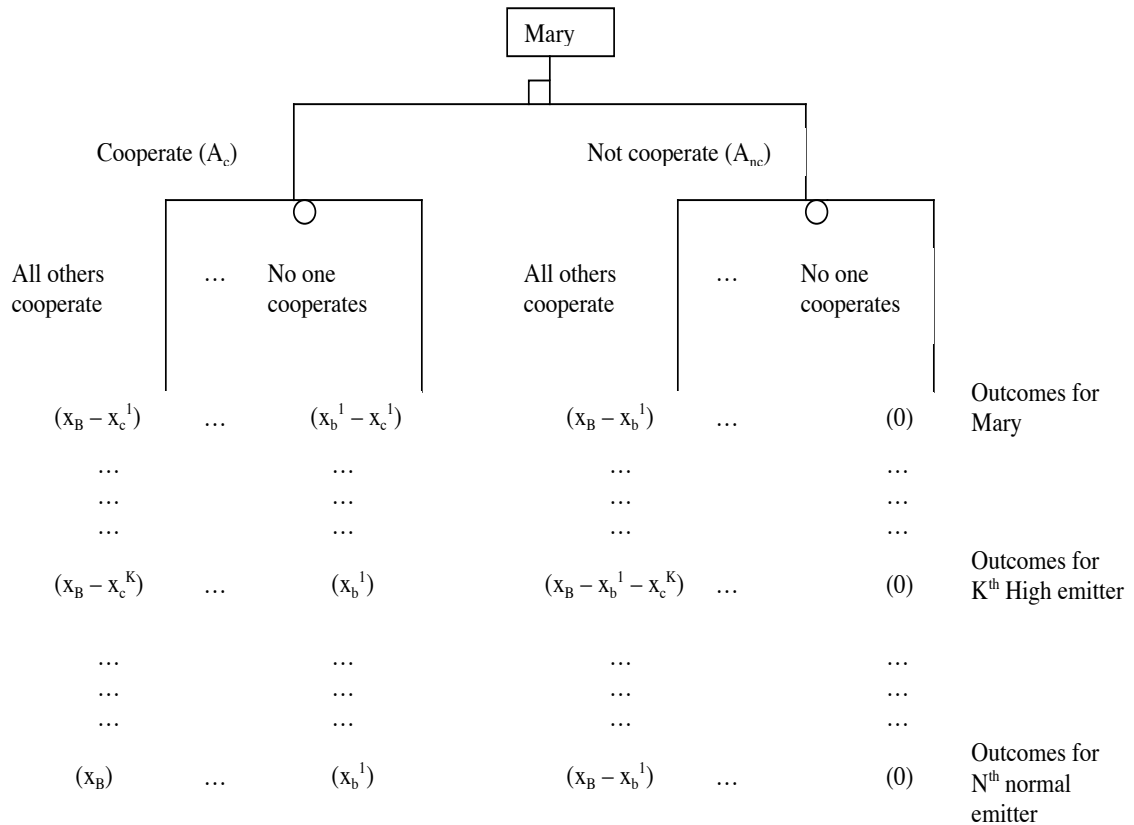| $(x_B - x_c^1 - x_p^1)$	…	$(x_b^1 - x_c^1 - x_p^1)$	$(x_B - x_b^1 + x_p^1)$	…	(x_p^1)	Outcomes for Mary
…		…	…		…	
…		…	…		…	
…		…	…		…	
$(x_B - x_c^K - x_p^K)$	…	$(x_b^1 + x_p^K)$	$(x_B - x_b^1 - x_c^K - x_p^K)$	…	(x_p^K)	Outcomes for Kth High emitter
…		…	…		…	
…		…	…		…	
…		…	…		…	
(x_B)	…	(x_b^1)	$(x_B - x_b^1)$	…	(0)	Outcomes for Nth normal emitter
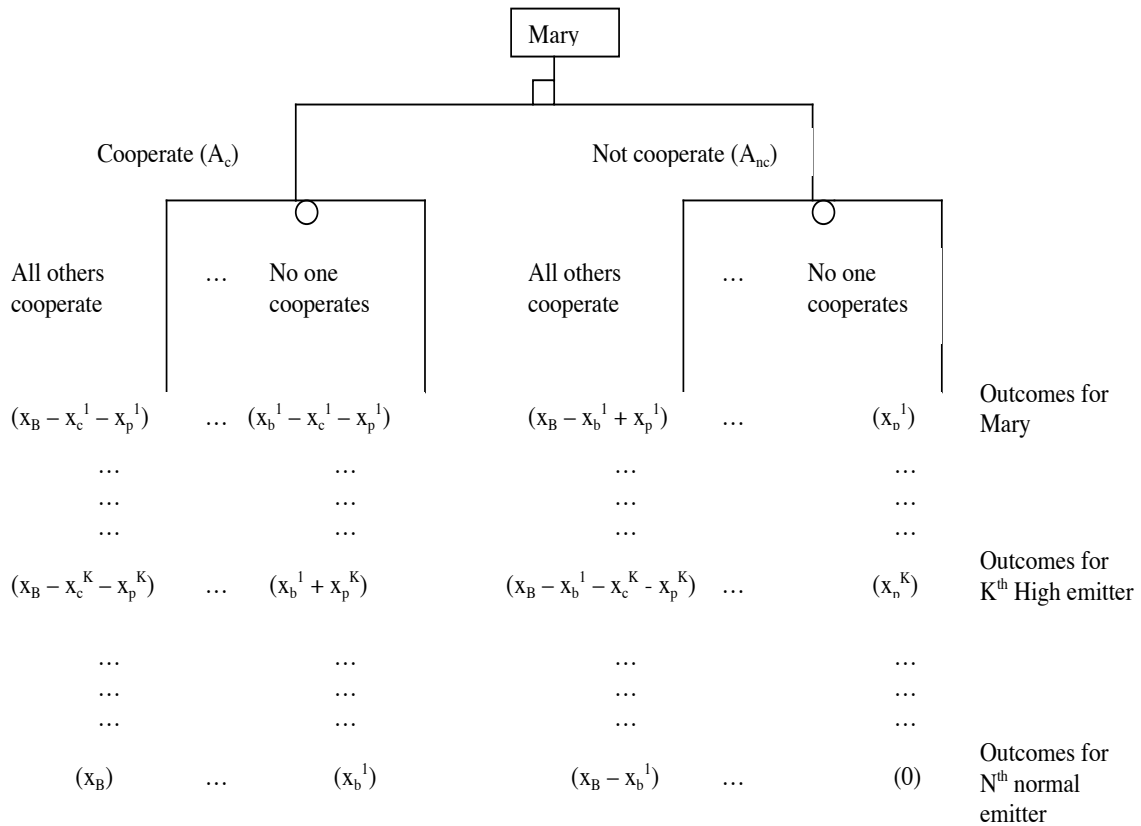
Figure 2.3: A generalized decision tree representing the prisoners' dilemma game for provision of environmental goods under regulatory policy mechanisms

other hand, if $x_p < x_c$, then the outcomes in column 4 of figure 2.3 [(x_p^1), (x_p^K)] would reflect the Nash equilibrium and every player's dominant strategy will, as in the case of voluntary mechanisms, still be not to cooperate/contribute. Figure 1.3 in chapter 1 presents the detailed decision tree faced by a vehicle owner in Atlanta after the regulatory mechanism is introduced. This dissertation is focused on studying this particular regulatory mechanism, as shown in figure 1.3, because there are actions/strategies available to the high-emitting vehicle owners, which have $x_p < x_c$.

In the case of the Atlanta airshed, IM policy intervention is an example of a "regulatory mechanism". This mechanism is mandated under the 1990 Clean Air Act Amendments and has resulted in the institutional arrangements that include IM testing stations, IM repair stations, special departments in governmental agencies such as EPA, GA-DNR, and private contractors (such as Clean Air Force). The market institutions of automobile manufacturers, automobile dealers (especially dealers of used cars) are also affected by the IM policy intervention. Furthermore, the enforcement involves

governmental institutions such as traffic police, county vehicle registration authorities, and the state department of motor vehicles and safety (for a detailed list of affected stakeholder institutions in California's IM program please see (Bedsworth and Kastenberg 2002)). While I am not able to present in this dissertation details about all the institutions involved in Atlanta's IM program, my focus remains on four issues: (1) what is the high-emitting vehicle owners' decision behavior (μ_r) given the incentive structure of the regulatory mechanism (figures 1.3 and 2.3)? (2) what is the resulting outcome in terms of pollution reduction due to the decision behaviors of high-emitting vehicle owners? (3) from the perspective of the mechanism designer, are there other values, such as fairness, that influence the outcomes due to the regulatory mechanism of IM program? and (4) do fairness concerns also influence the cooperative and non-cooperative decision behaviors?

2.3: cooperative and non-cooperative decision behavioral research under the contextual conditions of voluntary and regulatory policy mechanisms

Experimental and quasi-experimental studies have been conducted in the past to estimate the probability of cooperative and non-cooperative behaviors of decision makers under various mechanisms, institutions and environments. Most of the experimental research has been conducted under voluntary mechanism designs (section 2.3.1 and figure 2.2); however some studies have also been conducted under regulatory (figure 2.3) and adaptive mechanism designs. Next, I review their major findings. During the review, my focus is primarily on a discussion of the contextual conditions that have been hypothesized by the (quasi-) experimentalists to increase or decrease the probabilities of cooperation within each of the mechanism/governance designs.

2.3.1: Cooperative and non-cooperative decision behaviors under the contexts of voluntary policy mechanisms:

Public goods games present one kind of voluntary experimental mechanism designs to study cooperative and non-cooperative decision behaviors. During the late 1970s and 1980s, pioneering experimental work in this area was done by the sociologist Gerald Marwell (Marwell 1982; Marwell and Ames 1979; 1980; 1981), the psychologist Robyn Dawes (Dawes 1975; 1980; Dawes, McTavish et al. 1977; 1986), the political scientist John Orbell (Orbell and Dawes 1981; 1991; 1993; 1990; Orbell, Schwartz-Shea et al. 1984), and the economists Marc Isaac and James Walker (Isaac, McCue et al. 1985; 1988; Isaac and Walker 1988a; 1988b; Walker 1978; 1980; Walker, Gardner et al.

1990). Since the early 1990s, most of the experimental research has focused on ascertaining the contextual conditions that affect the probability of cooperation. Following is a common variant of the experimental game under controlled laboratory conditions (Ledyard 1995: 113): "Four male undergraduates from a sociology course are brought to a room and seated at a table. They are each given an endowment of $5. They are then told that each can choose to invest some or all of their $5 in a group project. In particular, each will simultaneously and without discussion put an amount between $0 and $5 in an envelope. The experimenter will collect the "contributions", total them up, double the amount, and then divide this money among the group. The private benefit from the public goods, in this case, is one half the total contributions, which is what each receives from the group project. No one, except the experimenter, knows others' contributions, but all know the total. The procedure is implemented and the subjects are paid. The data collected, beyond the description of experimental parameters, is simply *the amount contributed by each individual* (my italics)."[32]

What will be the expected outcome of this experiment? The economists/game theoreticians will predict that no one will ever contribute anything (i.e. the probability of contribution/cooperation will be zero %) because the expected value of the non-cooperative strategy dominates the cooperative strategy, no matter what other players play. The individual self-interest is at odds with the group interest under this theory. On the other hand, socioliogists/psychologists predict that each subject will contribute something. They claim that altruism, social norms or group identification will lead each to contribute $ 5, the group optimal outcome. According to this theory, there is no conflict between individual and group interest.

The findings from major/pioneering experiments suggest that neither theory is right. Generally, total contributions lie between $8 and $12, or 40% to 60% of the group optimum. Dawes and Thaler (1988) state: "it is certainly true that there is a 'free rider problem'….On the other hand, the strong free rider prediction is clearly wrong." Ledyard ascribes these confounding results to the lack of control of specific experimental factors in many studies. According to Ledyard (1995: 115), the generic experiment described above is "neither particularly elegant nor carefully controlled. Even so, at least twelve

---

[32] The dependent variable in all of the public goods games is thus "the amount of contribution", which in other variants of prisoners' dilemma games is assumed to equate with "the amount/extent of cooperation".

major choices have been made in creating this design: (1) the number, (2) gender, and (3) education of the subjects, (4) whether they are face to face or acting through computer terminals or in isolated rooms, (5) how much endowment to give to each and in what form (cash, tokens, promises,…), (6) whether discussion is allowed and in what form, (7) whether contributions are private or public, (8) by how much to increase the total contributions, (9) how to divide up the larger pie (for example, in proportion to contribution or to number), (10) whether or when to announce the results, (11) whether to pay subjects publicly or privately, and finally (12) whether to run the procedure once or, say, 10 times. Each of these choices represents a potential treatment or control. Each treatment has been shown by at least one experimenter to have a significant effect on the rate of contribution." In addition, there are some other intangible factors that are difficult to control, which include the history and experience of the subjects, the beliefs and risk attitudes of the subjects.

Six pioneering public goods experiments were reported by Bohm (1972), Dawes et al. (1977), Marwell and Ames (1979), Isaac and Walker (1984), Isaac et al. (1985) and Kim and Walker (1984). All of them found that the rate of contributions in the initial period ranged between 41% and 71% of the Pareto optimum/efficiency level. The economists found that probability of contribution/cooperation significantly decreases with repetition (Isaac, McCue et al. 1985; Isaac and Walker 1984; Kim and Walker 1984); while sociologists/psychologists found the cooperation increases with communication (Dawes, McTavish et al. 1977; Marwell and Ames 1979). Economists found that in the last period contribution declined to a range of 8% and 19% under repetitive contextual conditions; while sociologists/psychologists found that contribution rate increases up to a range of 72% to 81% under communicative contextual conditions. Economists/game theoreticians could not show experimental finding with 0% contribution rate; nor sociologists/psychologists could show a finding with 100% contribution rate, which is the group/Pareto optimum in these designs.

Table 2.1 presents a summary of experimental research under voluntary mechanisms and shows 19 individual-level contextual conditions that controlled lab experimentalists hypothesize to potentially affect the percentage of contributions as a percentage of Pareto-optimum/efficient contribution levels. No single experiment has simultaneously controlled for all of these contextual conditions, while some of them remain untested to date. The interaction effects are also untested. I discuss the effect of

contextual conditions on percentage contributions in the following order, as shown in table 2.1: (i) strong effects that are replicable and experimentalists have (mostly) consistent findings, (ii) weak effects that are relatively difficult to replicate and findings are not very consistent, (iii) null/mixed effects that have either null effect or the effect appears to be cancelled out by inconsistent findings, and (iv) the effects that are difficult to control in experimental public goods games settings, and therefore not much is known empirically about them. Authors who tested or hypothesized about each of these effects are listed in the third column.[33]

Table 2.1: Individual level contextual conditions that affect the percentage of contributions for public goods under voluntary mechanisms: the hypotheses and findings of the controlled laboratory experimentalists

Contextual conditions	Hypothesized direction of effect on percentage contributions	Studies that tested/identified the effect and their findings: [+] means positive effect, [-] means negative effect, and [0] means null effect.
I. Strong effects		
Experience	Negative/null	Isaac et al. (1984)[-], Palfrey and Prisbrey (1993)[-/0], Marwell and Ames (1980) [0], Isaac et al. (1988)[0]
Repetition /iteration	Negative	Isaac et al. (1984, 1985, 1990)[-], Brookshire et al (1989a) [-], Kim and Walker (1984) [-], Brown-Kruse and Hummels (1992) [-], Banks et al (1988) [-], Sell and Wilson (1990) [-], Andreoni (1988b) [-] , Isaac et al (1990) [0], Palfrey and Prisbrey (1993) [0], Bagnoli and McKee (1991) [+], Isaac et al (1988) [-], Suleiman and Rapoport (1992) [-]
MPCR (Marginal Per Capita Return)	Positive	Isaac et al. (1984)[+], Isaac and Walker (1988b)[+], Kim and Walker (1984) [+], Brown-Kruse and Hummels (1993) [+], Isaac et al (1985) [+], Brookshire et al.(1989a), [+] Fischer et al. (1988) [+], Palfry and rosenthal (1991a) [+], Rapoport and Suleiman (1993) [+], Palfry and Prisbrey (1993) [+], Isaac et al (1990) [0]
Communication	Positive	Dawes et al. (1977) [+], Isaac et al (1985) [+], Isaac and Walker (1988a, 1991) [+], Chamberlin (1978) [0], Palfrey and Rosenthal (1991b) [0], Dawes et al 1987 [+], Orbell et al (1988, 1990) [+]
Economics training	Negative	Marwell and Ames (1981) [-], Isaac et al (1985) [-]

[33] Most of the economists showed contextual conditions that decrease the % contributions, while most of the sociologists and psychologists showed contextual conditions that increase % contributions.

Table 2.1 (continued)

2. Weak effects		
Heteroganeity (non-symmetry)	Negative	Marwell and Ames (1979, 1980) [0], Isaac et al (1985) [-], Bagnoli and McKee (1991)[-], Brookshire et al (1989a)[-], Fisher et al (1988)[-], Rapoport and Suleiman (1993) [-]
Common knowledge	Negative/null	Isaac and Walker (1989) [0], Brookshire et al (1989a) [-]
Thresholds	Positive	Marwell and Ames (1980)[0], Isaac et al (1984, 1988) [+], Dawes et al (1986)[+], Suleiman and Rapoport (1992)[+], Palfry and Rosenthal (1991a) [+/-], Rapoport and Suleiman (1993)[0],
Beliefs	Positive	Dawes et al 1977 [+], Orbell and Dawes 1991[+], Rapoport and Suleiman 1993[+]
Friendship/Group identification	Positive	Dawes et al (1977) [+], Orbell et al (1988)[+], Brown-Kruse and Hummels (1992) [+]
Rebates	Positive	Dawes et al (1986) [+], Isaac et al (1988) [+]
Unanimity	Negative	Banks et al (1988) [+/-]
3. Null/mixed effects		
Number of players	Zero/mixed	Marwell and Ames (1979) [0], Chamberlin (1978) [+], Bagnoli and McKee (1991) [+], Isaac et al. (1988) [0], Isaac et al (1990) [-]
Gender	Zero/mixed	Dawes et al (1977)[women +], Mason et al 1991[women +], Isaac et al (1985) [0], Poppe and Utens (1986) [0], Orbell et al (1992) [0], Brown-kruse and Hummels (1992) [men +]
4. Unmeasured effects		
Fairness, altruism	positive	Marwell and Ames (1979) [+]
Learning	Unknown	Not clearly tested.
Decision costs	Unknown	Dawes and Orbell (1982) [0]
Risk aversion	Unknown	Not clearly tested
Moral suasion	Unknown	Not clearly tested

I: Strong effects: Experience, repetition/iteration and economics training in subjects strongly decreases percentage contributions. Higher Marginal Per Capita Return (MCPR)[34] and communication among subjects strongly increases percentage contributions/cooperation.

If experience is measured by the yardstick of whether the subjects have previously participated in similar experiments, then some studies find that more experienced players/subjects contribute less, while other studies find that there is not much significant difference between the contributions made by experienced and non-experienced subjects. The data in Isaac et al. (1984) suggests that subjects who have

---

[34] Isaac and Walker (1984) define Marginal Per Capita Return (MPCR) as marginal rate of substitution of the private good (z_i) for the public good, $y = \sum c^k$. MPCR = - $(\delta u^i/ \delta y)/ \delta u^i/ \delta c_i)$, where $u^i = p (z-c_i) + a.y/N$.

previously been in a voluntary contribution experiment contribute less than those who are first-timers but still more than zero. Palfrey and Prisbrey (1993)'s data shows a negative direction of contributions for more experienced players but the effect is not statistically significant. Both Marwell and Ames (1980) and Isaac et al. (1988) controlled for experience of subjects and found no significant effect.

Repetition/iteration in the same game/experiment set up with no threshold levels causes the percentage of contributions to decrease significantly. This is confirmed by Isaac et al. (1985; 1984; 1990), Brookshire et al (1989a), Kim and Walker (1984), Brown-Kruse and Hummels (1993), Banks et al (1988), Sell and Wilson (1990), and Andreoni (1988b). However, Isaac et al (1990) and Palfrey and Prisbrey (1993) found no effect of repetition on percentage contributions in non-threshold environments. The experiments with threshold environments report confounding effects of repetition: Bagnoli and McKee (1991) report a positive effect, while Isaac et al. (1988) and Suleiman and Rapoport (1992) report a negative effect on the percentage contributions.

Marginal benefit of the public good compared to the private good is called "Marginal Per Capita Return"(MPCR), which is easily controllable in laboratory experiments. Isaac et al. (1984) and Isaac and Walker (1988b) found that as MPCR is increased, the percentage contributions also increase. Subjects therefore do appear to respond to incentive structures in a consistent way according to these two pioneering studies. The positive effect of increased MPCR has been confirmed by Kim and Walker (1984) and Brown-Kruse and Hummels (1993) under symmetric pay-off environments and Isaac et al. (1985), Brookshire et al. (1989a), Palfrey and Rosenthal (1991a), Rapoport and Suleiman (1993) and Palfrey and Prisbrey (1993) under asymmetric pay-offs. Isaac et al (1990) however report that increases in MPCR under large numbers of subjects do not significantly increase the percentage contributions.

Dawes et al. (1977) showed that permission of relevant communication among subjects increased contributions for public goods, which according to the hard-core game theory should not matter at all. Uniquely dominant Nash strategies should not be dependent upon whether subjects communicate or not and all forms of communication is nothing but mere "cheap talk", or at best "coordination-improving mechanisms". The experimental results however show categorically that communication improves cooperation/contributions and confirm the earlier findings of Dawes et al. (1977). Isaac et al. (1985) and Isaac and Walker (1991; 1988a) were not able to reject the positive effect

of communication on increased contributions. Only Chamberlin (1978) and Palfrey and Rosenthal (1991b) found no significant effect of communication on contributions. All the studies conducted by sociologists/psychologists found a positive effect of communication on contributions (Dawes, van de Kragt et al. 1987; 1990; Orbell, van de Kragt et al. 1988). The "cheap talk" theory of games stands discredited even in experiments conducted by economists. On the other hand, sociologists/psychologists hypothesize that communication improves cooperation because either "it provides an occasion for (multilateral) promises or because it generates group identity – or possibly some combination of those two hypotheses (Orbell et al. 1990: 619)." More research is needed to test explanatory hypotheses for the positive effects of communication on cooperation.

Marwell and Ames (1981) raised the question: are economists the only free riders? They found that contributions were significantly lower if and only if the subjects were graduate students in economics at Wisconsin. Economics training thus appears to reduce the percentage contributions. Isaac et al. (1985) compared economics undergraduate students from Caltech with sociology undergraduate students from Pasadena City college and found that, under iterative conditions, sociologists also tend to free ride at an increased rate as do the economists. It is however not clear in both studies how students in economics and sociology courses are totally randomly distributed from other aspects of their personalities. Further, it is not clear how one can exactly measure and define economics training and differentiate it from sociology.

II: Weak effects:

Marwell and Ames (1979; 1980) found no significant effect of heterogeneous endowments and asymmetric outcomes on the percentage contributions of subjects. On the other hand, Isaac et al. (1985) hypothesized and found that heterogeneous endowments and asymmetric outcomes/preference functions cause percentage contributions to decrease. The negative effect has been confirmed by Bagnoli and McKee (1991), Brookshire et al. (1989a) and Rapoport and Suleiman (1993), but it is not clear whether interaction of heterogeneity with other effects, such as common information and repetition, decreases or increases the percentage contributions.

The effect of common information (about the incentive structures of a public goods game) on percentage contributions is hypothesized to be negative; i.e. complete information about other players' payoff functions leads to higher contributions while incomplete information causes a decrease in contributions. Isaac and Walker (1989)

found no effect of common information on percentage contributions, while Brookshire et al (1989a) found that contributions tend to be less under complete information than under incomplete information environments. The interaction effects of information structures with other effects, such as heterogeneous payoffs and threshold levels, is less clear and not explicitly tested.

If a threshold level is set for the total contributions, then the hypothesis is that generally the percentage of contributions increases but the rate of attaining the threshold levels of contributions decreases. The experimental evidence is not so clear. Marwell and Ames (1980) report no effect of threshold levels on increased percentage of contributions, but Isaac et al. (1988; 1984), Dawes et al. (1986), and Suleiman and Rapoport (1992) report a positive effect of threshold levels on attaining more contributions. In the case of heterogeneous environments and asymmetric payoffs, Palfry and Rosenthal (1991a) find that setting up thresholds increases contributions in some cases and decreases them in other cases, but Rapoport and Suleiman (1993) find no effect.

"Beliefs about the world" (hardly testable) potentially make subjects commit mistakes in the game that results in higher contributions. It is difficult to design an experiment for testing the beliefs of subjects. Some experimentalists have attempted to model the effects of beliefs, such as beliefs about other players in the game (i.e. whether a cooperative subject believes other players to be more cooperative) by asking respondents survey questions (Dawes et al. 1977, Orbell and Dawes 1991, Rapoport and Suleiman 1993). The survey data has been rejected/questioned by a majority of the economists such as Ledyard (1995: 162), who states: "I would suggest that perhaps the (survey) data on beliefs and risk attitudes are unreliable and that before one rejects those [expected utility and altruistic] models one should try to find better ways to measure what is needed." Rapoport and Suleiman (1993), on the other hand, rejected both expected utility and altruistic models and argued that belief structures and risk attitudes of subjects (as measured through the survey data) powerfully explain the variation in percentage contributions.

Dawes et al. (1977) and Orbell et al. (1988) tested the hypothesis whether friendship or some form of group identification has positive effect on the contributions. Both studies found that friendship among subjects increases the rate of cooperation/contributions. Brown-Kruse and Hummels (1993) compared community

versus non-community groups and found a very small positive effect on the increased contributions for the groups comprised of similar community subjects. The precise measurement of friendship/group identification is still a hotly debated issue.

Rebates also increase the contributions (Dawes et al. 1986, Isaac et al. 1988). The decision rule of group unanimity[35] increases the contributions but there are so few success periods (about 13%) that the gain in potential contributions is outweighed by the failures (Banks et al 1988). More studies are needed however to establish the effect of group unanimity on percentage contributions.

III: Null/mixed effects: The number of participating subjects (and group sizes) is easily controllable in experiments. Theorists disagree whether increase in the numbers of subjects (as well as group sizes) positively or negatively affects the percentage contributions. Some argue that contributions decrease as subjects/group size increases because non-cooperative behavior is difficult to detect and therefore self-interested individuals will be less willing to contribute. On the other hand, other theorists hypothesize that a large number of subjects/group sizes increases the percentage contributions because the altruistic tendency of the subjects is reinforced in large groups. Marwell and Ames (1979) found no effect on percentage contributions with an increase in the number of subjects/group sizes, while Chamberlin (1978) and Bagnoli and McKee (1991) found a negative effect on contributions as the subject pool increased. The effect of the subject pool was more explicitly controlled and tested by Isaac et al. (1988) and they found no significant effect. On the other hand, Isaac et al. (1990) report a positive effect of large groups of subjects on percentage contributions, especially when marginal benefit from public goods is relatively higher. The results are confounding because it costs lots of money for experimentalists to pay extremely large subject pools[36] and no study has been attempted with more than 1000 subjects. The quasi-experimental study, attempted in this dissertation, involves samples as large as 500,000.

The effect of gender, which is easily controllable in lab experiments, on percentage contributions has mixed evidence. Some studies (Dawes, McTavish et al. 1977; Mason, Phillips et al. 1991) found women to be initially more cooperative (but

---

[35] Group unanimity requires that even a single veto will result in abandoning the public project.
[36] Some experimentalists have attempted to lie to the subject pools to indicate that they were in large groups. I think this distorts the results.

gender differences vanish in later iterations); while others (Isaac, McCue et al. 1985; Orbell, Schwartz-Shea et al. 1992; Poppe and Utens 1986) found no difference between men and women. Brown-kruse and Hummels (1993) also found no significant differences between men and women in their total contributions but they found that men contributed at higher rates than did women. The findings on gender effects are still inconclusive.

IV: Effects with not much experimental data: If "fairness" is defined as "equal percentage of contributions for each player", then how do concerns for fairness affect the percentage of contributions? Marwell and Ames (1979) suggest that concerns for fairness are important mediating factors in investment decisions for public goods, when fairness is defined as a question "what is fair percentage of contribution for each player?" Marwell and Ames (1979) found that subjects less "concerned with fairness" (measured through survey of experimental subjects) contributed less in public investments. This finding still needs to be re-tested.

On the other hand, most of cooperative game theory defines fairness by asking the question: what is the fair allocation of outcomes among the subjects if they decide to cooperate (Aumann 1987)?" Not much experimental work has been done to study the effect of fairness in the context of public goods games either from the perspective of fair contributions and/or fair allocations, primarily because it is extremely difficult to measure the "concerns for fairness" and it is ambiguous how to precisely define what is fairness (Stone 1997).[37]

The effects of learning on percentage contributions are not well understood because it is difficult to segregate them from history, experience, repetition and strategy effects. From the perspective of game theory, players "learn" to become selfish Nash players, while sociologists argue that players "learn" to become better altruistic group

---

[37] I test indirectly the effects of fairness on the odds of cooperation in this study. I use group-level contextual variables to test the hypothesis whether cooperative and non-cooperative high-emitting vehicle owners systematically come from different income-level and racial neighborhoods/census block-groups. If the odds of cooperative vehicle owners coming from systematically higher income-level white neighborhoods are high, then it can be inferred that concerns for fairness improves the rate of contributions/repair costs. Conversely, if the odds of non-cooperative vehicle owners coming from systematically lower income-level black neighborhoods are high, then it can be inferred that concerns for unfairness decreases the rate of contributions/repair costs.

members. Both the theories have opposite predictions but no experiment clearly tests the effects of learning, primarily because learning cannot be measured/segregated.

The effect of "decision costs" and "risk aversion levels" on the percentage contributions are also under-researched areas and it is not clear how they affect the cooperative and non-cooperative decision behaviors. Decision costs occur due to concerns raised by the theory of bounded rationality in the backdrop of computational and informational complexity (Simon 1982). Dawes and Orbell (1982) found no significant difference in the percentage contributions between two groups of subjects who had 5 minutes and 24 hours respectively to think before taking a decision. It is however possible that "precise optimization carries cognitive processing costs which are traded off by subjects against rewards: the lower the rewards the more errors in computation (Ledyard 1995: 167)." This hypothesis has not been directly tested in experimental research.

Another hypothesis that remains untested concerns the effect of the subject's risk attitude on the percentage contributions.[38] The problem in experimental economics remains how experimentalist can measure the preference function of their subjects? This measurement problem makes it difficult to model experiments controlling for risk averse, risk neutral and risk-taking subjects.

The effect of *moral suasion* concerns the indirect/intangible effect of experimentalist on the belief/value structures of subjects. An experimentalist, while giving the directions for the experiment to the subjects, may hint at the optimal strategy that may cause experiments conducted by economists to have lower contribution rates while by sociologists to have higher contribution rates.[39] Future research in experimental economics is expected to test the effects of fairness, decision costs, risk aversion levels and moral suasion on the percentage of contributions for public goods. Compared to the voluntary mechanism designs, the study of cooperative and non-cooperative decision behaviors under the contextual conditions of regulatory policy mechanisms is relatively newer area of research that I discuss in the next section.

---

[38] I discuss the details of individuals' decisions under risk and uncertain conditions in chapter 3.
[39] I think the effect of moral suasion can be measured by a meta-analysis of the data collected in experimental studies in different departments (economics, sociology, political science, psychologists). Analysis of the set of directions is also important from this viewpoint.

2.3.2: Cooperative and non-cooperative decision behaviors under the contexts of regulatory policy mechanisms:

A growing number of the field studies evaluating the effectiveness of environmental regulations have taken a close look at compliant and non-compliant behaviors of individuals and organizations. It is relatively easier to evaluate the compliant and non-compliant behaviors of organizations because they are "stationary" (though the measurement of pollutants still poses a huge implementation problem). On the other hand, evaluating compliant and non-compliant behaviors of individuals is relatively difficult because they are "mobile/non-point" sources of pollution. Evaluation of compliant and non-compliant vehicle owners is one example of mobile sources of regulated pollution that is attempted in this study and I devote a considerable part of chapter 4 to reviewing this particular aspect of decision behavior under regulatory mechanisms.[40] Agricultural farmers provide another example of mobile sources of pollution because it is difficult to measure the effect of agricultural/nutrient runoffs from individual farmers on the observable water pollutant levels.

Previous empirical studies that have evaluated the compliance and non-compliance rates of organizations with the environmental regulations have two (not exactly compatible) findings: The first group observes that firms only comply (and pollute less) when environmental regulations exist and are strongly enforced. If pollution abatements actions are voluntary or weakly enforced, firms keep on polluting (Gray and Scholz 1993; Helland 1998; Kuperan and Sutinen 1998; Segerson and Miceli 1998). The second group observes that regulatory enforcement is not a necessary condition for obtaining compliance (and pollution below regulatory standards) by all firms. Some firms "go beyond" regulatory minimums (Arora and Carson 1996; Prakash 2000) and "over-comply" (DeHart Davis 2000), while others take action in the absence of specific regulations or strong enforcement (Gunningham, Kagan et al. 2003; Haines 1997;

---

[40] I do not use the term compliant and non-compliant behaviors because of two overarching reasons: First, some people can be compliant but non-cooperative (such as migrated fail group of vehicle owners) as well as non-compliant but cooperative (such as a high-emitter who actually repairs the vehicle as per IM rules but still always fails the emissions test) according to the definitions of cooperative and non-cooperative behavior presented in sections 1.3 and 1.4. Second, there are linguistic effects. I hope that the use of cooperative and non-cooperative behaviors will reflexively lead to a positive image of the polluters and not just a negative image implied in the name compliant and non-compliant behaviors. Nevertheless, broadly speaking, cooperative and compliant may be treated as synonyms except for some extreme caveats mentioned above.

Harrison 1999; King and Lenox 2000; Welch, Mazur et al. 2000). May (2003) hypothesizes that there are three underlying motivations for regulatory over-compliance by the firms: (1) the deterrent fear associated with being found in violation of regulatory requirements, (2) a sense of civic duty, and (3) a social motivation that arises from peer and other social pressures. Prakash (2000) argues that reputation effects are among the strongest motivations for over-compliance.

The polluters contributing mobile sources of pollution, including high-emitting vehicle owners, may not have to worry about reputation effects as much as the firms need to. The deterrence fear, sense of civic duty and social motivation may have a stronger effect in the case of cooperative vehicle owners. But then it is not clear why non-cooperative vehicle owners will have low deterrence fear, sense of civic duty and social motivation. These questions are interesting future qualitative research questions but beyond the scope of this dissertation.

2.4: adaptive environmental policy mechanisms

I am introducing the concept of "adaptive mechanisms", which is actually based in the theoretical frameworks of "adaptive management" and "adaptive games". The adaptive management framework is understood as based on an experimental attitude toward environmental valuation and decision-making (Norton and Toman 1997). Adaptive management theorists propose that policy-makers often have to act under uncertainty, so policies should be designed as probes of the system, capable of reducing uncertainty for the future through social learning (Gundersen 1995; Gunderson and Holling 2002; Gunderson, Holling et al. 1995; Holling 1978; Holling 1992; Lee 1993; Norton and Steinemann 2001; Walters 1986). The theorists of "adaptive games" also emphasize the concept of learning by players (Broseta 2000).

Learning can work both ways: if a high-emitting vehicle owner learns how best to cheat the regulatory mechanism, then learning may have over-all negative repercussions at the societal level. On the other hand, if a mechanism designer learns that the existing mechanisms result in outcomes that are not collectively desirable, then perhaps new mechanisms can be "adaptively" instituted through policy changes that help attain the outcomes that are socially desirable. Norton (in press) elaborates in detail how policies can be adapted -- even in the face of uncertainty -- given the social and scientific learning that is constantly undertaken in human societies.

Adaptive mechanisms focus on real world situations. Reality is perceived at multiple spatio-temporal scales. The contextual conditions that effect the cooperative and non-cooperative decisions occur at multiple ecological scales. Further the contexts are nested within multiple ecological scales. An individual-scale context may affect as much the individual's decision behaviors as the group-scale contexts. Group-scale context may be measured/observed at various hierarchical spatio-temporal boundaries, such as residents of north Atlanta may differ from south of Atlanta, residents of Georgia may differ from the residents of Washington, residents of the USA may differ from the residents of India, and so on. Perception of the same individual from one ecological scale to another scale, and one context to another context, makes the contextual conditions nested within each other and dynamic in character. The multiple-scaled contextual differences, in my view, have a significant affect on the decision behaviors of individuals under uncertain and risky situations.

It will be a very difficult study to evaluate the decision behaviors under all the hypothesized multi-scaled contextual conditions. In this study, for the purposes of simple demonstration, I use two scales of contextual parameters to test the differences between cooperative and non-cooperative decision makers in the Atlanta region between 1997 and 2001 (See chapter 5 for more details on the research design). In chapter 4, I present contextual details of the regulatory mechanism in the Atlanta airshed that aims at reducing vehicular emissions from high-emitting vehicles by requiring their owners to carry out periodic testing and maintenance of the emission control systems on their vehicles. Analysis of individual- and group-scaled contextual conditions, and their effect on cooperative and non-cooperative decision behaviors, is an important analytical tool of adaptive environmental policy mechanisms.

However, before I focus on contextual details of Atlanta airshed, it is important to review the MCDM literature in normative and descriptive decision theories that relaxes the assumption of commensurable values. This is because in real world "adaptive" decision making situations decision makers use multiple non-commensurable values to evaluate alternate courses of actions and states of the world and use these evaluations to make their decisions. The case of outcomes measured on multiple non-commensurable values is presented in chapter 3.

CHAPTER 3

DECISIONS UNDER UNCERTAINTY ENTAILING MULTI-VALUED OUTCOMES: TOWARDS META-DECISION MODELS FOR DESIGNING ENVIRONMENTAL POLICY MECHANISMS

3.1: The expected value hypothesis and outcomes measured through multiple values: defining meta-decision problems

Multi-criteria decision making models (MCDM) present one methodology to characterize multiple values, such as efficiency and fairness, in evaluating public policy outcomes on multi-dimensional value scales. MCDM is a normative decision theory. At the same time, public policy evaluations are also concerned about knowing which values do actual decision makers take into account to measure the outcomes of their actions. This is known as the "ontological" research question of descriptive decision theorists. In real world policy problems, however, we cannot separate normative from descriptive decisions.

Decision theory is mostly classified in two categories: descriptive and normative (Cleveland 1973; Corner, Buchanan et al. 2001; Gal, Stewart et al. 1999; Hwang and Yoon 1981; Kahneman and Tversky 1979; 1968; Weiss and Bucuvalas 1980; Winterfeldt and Edwards 1986; Zeleny 1982). These classifications are based on Hume's thesis that descriptive facts are separate from normative values (Hume 1777/1955). Most decision theorists share the ontological commitment that they can potentially discover an optimizing decision algorithm that can either describe how people *make* decisions, or prescribe how people *should make* decisions. Due to this ontological commitment, they have created many descriptive and normative decision algorithms. I contend, however, that description and prescription are two facets of the same decision *process* (Norton in preparation) and that (1) each descriptive decision algorithm, in order to formally and precisely describe the decision behavior, and (2) each "normative" decision algorithm –

in order to arrive at a final "correct" recommendation -- makes *a priori* methodological assumptions for deciding the following four meta-decision problems:

(i) Which values are/should be included in the criteria set of evaluation to measure the outcomes of our actions? Is the value set compact and closed or is it non-compact and open? Do human societies only care for the values of cost-effectiveness, fairness, efficiency, social justice and environmental preservation in evaluation of any environmental policy decision; or there are/should be some additional values such as eco-system health, animal welfare that are/should also (be) included in the evaluation process. Concisely, what is the logic of a meta-choice that a value is/should be included in the criteria set of evaluation? In the rest of the dissertation, I refer to value ambiguity as a meta-decision problem of the criteria set. (ii) What is the logic of the meta-decision by which an alternative is included in the set of policy alternatives? This is referred to as the meta-decision problem of the alternative set. (iii) Given the multiplicity of decision models and algorithms, we are confronted with the problem of how to choose which descriptive or normative decision rule/algorithm to apply in a given situation. I call this a meta-decision problem for determining the decision rule set. (iv) How shall the weights be assigned to the pluralistic values on the basis of which we judge actions/decisions? I call this the meta-decision problem of weighting methodology.

Next, I present the formal version of each of the four meta-decision problems of choosing the criteria set, alternative set, method set and weighting methodology and then analyzing the assumptions made about these four meta-decision problems in descriptive and normative decision theories.

I define $A \neq \varnothing$ as a non-empty set of alternative paths (also called policies, actions, strategies or feasible solutions) of a decision problem.[41] Further I define a multi-criteria outcome function f as follows:

(3.1): $f : A \rightarrow R^x$

Each function $f_k : A \rightarrow R$ with $f_k (a) = z_k$ $(k \in \{1,...,x\}, a \in A)$ and $f (a) = (z_1,...,z_x)$ is defined as a multiple value function. In the most general sense, $\varphi = (A, f)$ is defined as a multiple criteria decision-making (MCDM) problem.

---

[41] The set of alternatives is always non-empty because the alternative of "no action" is always an alternative in any decision problem. Further, alternative paths include both the actions and events/states of the world, as defined in section 1.2.

(i) The first meta-decision problem concerns whether the set of alternative paths *A* is a finite set (as defined by Multiple Attribute Decision Making (MADM) theorists) or is it infinite (as defined by Multiple Objective Decision Making (MODM) theorists) or is it fuzzy (as defined by Fuzzy set theorists). Further, what meta-criteria should be used to include or exclude an alternative path from *A*?

(ii) The second meta-decision problem concerns the decision as to which value/criteria z_k *(k ∈ {1,…,x})* shall be included in the multiple value function of equation 3.1. Restricting the value set *z* to 1 element concatenates the MCDM problem to a scalar problem.[42] In the case of $x \geq 2$, we have a multiple-value decision problem. The meta-decision problem remains: which values shall be included in the evaluation function *f* to determine the desirability of actions faced by decision makers?

(iii) The third meta-decision problem concerns which weighting methodology shall be used to weigh the $x \geq 2$ values. Should the value trade-offs be set up as a zero-sum game with $\sum_{h=1}^{x} w_h \cdot z_h = 1$ or a positive-sum game with $\sum_{h=1}^{x} w_h \cdot z_h > 1$? Furthermore, which methodology should be used to ascertain the values of the weights w_h for the criteria z_h (where $h = 1,…,x$) ? (iv) The fourth meta-decision problem concerns which decision rule (decision algorithm, decision method) shall be used to solve the decision problem $\varphi = (A, f)$.

Both descriptive and normative decision theories face the aforementioned four meta-decision problems. The expected value/expected utility hypotheses, introduced in section 1.2, assume *a priori* answers to the four meta-decision problems when decision-makers measure outcomes on multiple value dimensions. In section 3.2, I briefly review the state of expected value/expected utility hypotheses in the light of meta-decision problems confronted in descriptive decision theory. Section 3.3 presents the state of EV/EU hypotheses in the light of meta-decision problems in normative decision theory. In section 3.4, I introduce the concept of Meta-Decision Models (MDMs) that are used to evaluate the impacts/outcomes of environmental policy decisions on multiple value dimensions. The MDMs operate interactively and simultaneously at two levels: At the level of action, multiple valued outcomes of our real world decisions are measured and

---

[42] As discussed in chapter 2, the cost-benefit function concatenates any decision problem with multiple valued outcomes to a single valued outcome. All the values are thus represented by monetary units, which are *commensurable* scalar quantities.

evaluated. The policy designer aims to describe the current state of outcomes that ensue from our decisions. At the level of reflection, the policy designer undertakes a normative analysis to determine where we are (in terms of multiple valued outcomes measured as a function of decision behaviors at the level of action) and where we want to be (measured in terms of multiple valued outcomes desired at the spatio-temporal horizon of an environmental policy decision problem). The concept of adaptive environmental policy mechanisms (elaborated in section 2.4) is also revisited in the light of meta-decision models. Hwang and Yoon (1981) present description of 12 decision rules that are more often discussed in normative decision theory to solve decision problems that involves measurement of outcomes on multiple value dimensions[43].

3.2: The expected value hypothesis and descriptive decision theory

Camerer (1995) provides an excellent review of experimental research that has been conducted in the area of descriptive decision theory. In particular, he elaborates seven decision theories that systematically differ in their description of human decision-making processes under conditions of risk and uncertainty. Especially, the shape, form and informational requirements of decision makers' utility/value functions systematically differ among the seven descriptive theories. Table 3.1 lists each of the seven decision theories and presents their respective hypotheses about the functional form of decision makers' utility/value functions that are proposed to describe the decision making process of individuals for measuring the expected value of different decision alternatives under uncertain and risky states of the world. Note that all of these seven theories are based on *probabilistic* accounts of measuring the expected utility/value. Zadeh's fuzzy decision theory is based on *possibilistic* or modal logic, which I briefly discuss after elaborating table 3.1.[44]

Equation no. 3.2 in table 3.1, which shows continuous and concrete functional forms of expected utility hypothesis, is discussed in section 1.2 of the dissertation. The first major challenge to EV/EU hypotheses came at a symposium in Paris in 1952, where Maurice Allais presented an initial version of the so-called "Allais paradox" (Allais 1953;

---

[43] Hanne (2001) suggests that there are about 135 decision rules/algorithms in MCDM normative decision theory. Discussing each of them would require another dissertation.

[44] An interesting meta-decision problem concerns whether probability theory and fuzzy/modal logic are complementary or competitive. Zadeh (1995) argues that they are complementary, while Laviolette et al. (1995) argue that they are competitive. This is an interesting area of research in meta-decision theory, but beyond the scope of this dissertation.

Allais 1979). One of the most famous Allais examples illustrates a "common consequence effect" that is a consequence of EV/EU hypotheses. Subjects choose between A_1 and A_2, where A_1 = 1 million francs and A_2 = 0.1 probability of 5 million francs, 0.89 probability of 1 million francs, and 0.01 chance of 0 francs[45]. Subjects also choose between B_1 = 0.11 probability of 1 million francs, and 0.89 probability of 0 francs; and B_2 = 0.1 probability of 5 million francs, and 0.9 probability of 0 francs[46]. The EU hypothesis of equation 3.2 predicts that if (risk-averse) subjects prefer A_1 over A_2, then they should also prefer B_1 over B_2; and if they (risk-takers) prefer A_2 over A_1, then they should also prefer B_2 over B_1. This is the "common consequence effect" of EV/EU hypotheses in equations 1.3, 1.4 and 3.2. Allais hypothesized that subjects' preferences over uncertain/risky choices were not consistent, as assumed by EV/EU hypotheses and predicted by common consequence effects. Actually the most frequent choice pattern of subjects in experiments – $A_1 > A_2$ and $B_2 > B_1$- violates the consistency requirements of EV/EU hypotheses, which is Allais paradox.

Table 3.1: Predictions of 7 descriptive decision theories about the functional form of decision-makers' MCDM utility functions (adapted from Camerer 1995: 631)

Decision theory	Equation no.	Continuous, $U^* (F(x))$	Discrete, $U^* (\sum p_i x_i)$
Expected utility	3.2	$\int u(x)dF(x)$	$\sum p_i u(x_i)$
Weighted utility	3.3	$[\int u(x)w(x)dF(x)]/[\int w(x)dF(x)]$	$[\sum p_i w(x_i)u(x_i)]/[\sum p_i w(x_i)]$
Implicit expected utility	3.4	$\int u(x, U^*)dF(x)$	$\sum p_i u(x_i, U^*)$
Fanning-out hypothesis	3.5	$[\{-U''(x;F)\}/\{U'(x;F)\} \geq \{-U''(x;G)\}/\{U'(x;G)\}]$ if $F(x) \leq G(x)$ for all x	Not applicable
Lottery dependent utility	3.6	$\int u(x, c_F)dF(x)$ $c_F = \int h(x)dF(x)$	$\sum p_i u(x_i, c_F)$ $c_F = \sum h(x_i)p_i$
Prospect theory	3.7	Not applicable	$\pi(p_x)v(x) + \pi(p_y)v(y)$ if $p_x + p_y < 1$ or $x < 0 < y$; and $(1- \pi(p_y))v(x) + \pi(p_y)v(y)$ if $p_x + p_y = 1$ or $y < x < 0$
Rank dependent utility	3.8	$\int u(x)d[g(F(x))]$	$\sum_{i=1}^{n} u(x_i)[g(\sum_{j=1}^{i} p_j)- g(\sum_{j=1}^{i-1} p_j)]$

[45] $EV(A_1) = 1$ is sure bet, while $EV (A_2) = 0.1x5 + 0.89x1 + .01x0 = 1.39$ is a risky bet; but note that $EV (A_2) > EV (A_1)$, which means that EV hypothesis will predict that a (risk-taking) rational agent should choose A_2.
[46] $E(B_1) = 0.11$, while $E (B_2) = 0.5$. Note that $E (B_2) > E (B_1)$.

The Allais paradox was replicated by other researchers in experimental settings. MacCrimmon (1965) reported about 40% EV/EU violations. Morrison (1967) reported about 30% violations, while Slovic and Tversky (1974) found 60% violations. Slovic and Tversky (1974) even presented written arguments to the experimental subjects that listed pros and cons of EV/EU. After reading both arguments, slightly more subjects switched their choices to become more inconsistent with EU than becoming consistent![47]

A second serious challenge to EV/EU hypotheses was posed by psychologists, which are known in the literature as "process violations". In many experiments, subjects appear to use decision making procedures or processes that are much simpler than EV/EU. For instance, in one study the value of gambles was better predicted by an *additive* combination of probability and outcomes than by their *products*[48] (Slovic and Lichtenstein 1968). Tversky (1969) showed that subjects chose intransitive outcomes, and this finding has been recently reconfirmed by Loomes et al. (1991). Payne (1976) found that subjects even did not seek information about all the alternatives before making their decisions, which suggests that the descriptive process of decision-making among subjects is not the one suggested by EV/EU hypotheses.

Thirdly, many researchers have discovered systematic biases in elicitation of utility functions. Hershey and Schoemaker (1980) found that substantially more subjects preferred a loss of $10 to a gamble of losing $1000 with a probability of 1% *when it was called an insurance premium than when it was unlabeled*. Hershey and Schoemaker (1985) also found that utility functions elicited using probability and certainty equivalents were systematically different, violating the assumption that utility is invariant to the procedure used to elicit it.

As researchers began to question the empirical validity of the EV/EU hypotheses, others have proposed many alternative descriptive decision theories. Table 3.1 shows six of them, each of which, in a sense, is a broader generalization of EV/EU hypotheses, relaxing one or the other foundational axioms of EV/EU theory. The problem is that some of these alternative descriptive decision theories are not as easily testable as EV/EU theory is.

---

[47] MacCrimmon and Larsson (1979) review in detail the experimental tests conducted to check the emergence of Allais paradoxes under different parametric choices of outcomes/lotteries and found Allais paradox to be robust.

[48] EV/EU hypotheses assume that subjects *multiply* probabilities with their outcomes.

Equation 3.3 in table 3.1 shows weighted utility theory proposed by Chew (1983). This theory relaxes the axiom of independence of EV/EU theory and proposed a "weak independence" axiom.[49] Note that the weighted utility theory proposes that the utility of a gamble/alternative is a normalized *linear* function of the expected probabilities and weights of the utility functions over specific outcomes.

Dekel (1986) proposed "implicit Expected Utility" [equation 3.4 in table 3.1], which also depends upon a weakened form of the independence axiom called "betweenness".[50] The utility function $u(x_i, U^*)$ in equation 3.4 denotes the utility of an outcome x_i, but the utility function used to evaluate x_i depends upon an implicit utility function U^*. Note that "implicit expected utility" also proposes linear preference functions, though they need not be parallel as EV/EU and weighted utility theory has assumed.

Machina (1982) proposed a *fanning out hypothesis* (equation 3.5 in table 3.1) that suggests that people are more risk averse towards gambles that are better in the sense of stochastic dominance. Beckar and Sarin (1987) proposed *lottery dependent* utility theory (equation 3.6 in table 3.1) which suggests that the utility functions are exponential in form. Indifference curves fan out in the exponential form and lottery dependent preferences are quasi-convex if $h(x)$ is concave. Quiggin (1982) and Segal (1989) proposed *rank-dependent* utility theory (equation 3.8 in table 3.1). This theory suggests that cumulative probabilities are weighted functions, and the utilities of outcomes are weighted by the differential in the weighted cumulative probability. The weight of an outcome depends on its probability and its rank order in the set of possible outcomes. Note that if $g(p) = p$ in equation 3.8, the bracketed expression reduces to p_i, and equation 3.8 reduces to EU hypothesis of equation 3.2.

The most generalized hypothesis about the form of utility functions is presented by Kahneman and Tversky (1979) in their prospect theory (equation 3.7 in table 3.1). This theory suggests that indifference curves may vary with the choice of the reference point. The shape of the utility functions depends on $\pi(p)$, which is suggested to be a non-linear function in the extreme outcomes and more linear in mixed/non-extreme

---

[49] The weak independence axiom states that if a decision maker prefers the outcome x_i over x_j (i.e. $x_i > x_j$), then for all p in [0,1] there exists a unique q in [0,1] such that decision-maker should choose $p(x_i) + (1-p)x_k > q(x_j) + (1-q)x_k$ for all x_k.
[50] The axiom of "betweenness" states that if a decision maker chooses $x_i > x_j$, then s/he should also choose $p.x_i + (l-p)x_j > x_j$ for all p in [0,1]. Betweenness implies neutrality toward randomization among equally good outcomes.

outcomes. Kahnemann and Tversky's prospect theory thus suggests that respondents act as expected utility maximizers in non-extreme outcomes, but the violations of EU/EV become strong as extreme outcomes are presented to the respondents.[51]

A review of seven descriptive decision theories, as summarized in table 3.1, suggests that most of the furor in descriptive decision theory centers around finding a correct functional form and arguments of the utility functions of decision makers. From a meta-decision theoretical perspective, I propose that the assumption of fixed and given preference functions should be abandoned. Preference functions are spontaneously constructed (Slovic 1995), reversible (Kahneman and Tversky 1982) and context-dependent and dynamic (Norton, Costanza et al. 1998; Norton 1991; 1994).

Zadeh's (1965; 1968; 1973; 1995) fuzzy decision theory is specifically designed to be context-dependent. Fuzzy set theory is based on the assumption that probability theory is not sufficient by itself for dealing with uncertainty and imprecision that we observe in real world decision making contexts. Zadeh (1986; 1995) provides the following limitations of probability theory (which has been a cornerstone of all the other seven descriptive decision theories reviewed above): (1) Probability theory does not support the concept of a fuzzy event.[52] (2) Probability theory offers no techniques for dealing with fuzzy quantifiers like *many, most, several, few*. (3) Probability theory does not provide a system for computing with fuzzy probabilities expressed as *likely, unlikely, not very likely*, and so forth. (4) Probability theory does not provide methods for estimating fuzzy probabilities. (5) Probability theory is not sufficiently expressive as a meaning representation language. (6) The limited expressive power of probability theory makes it difficult to analyze problems in which the data are described in fuzzy terms. Zadeh (1995: 274) categorically states that "classical probability theory has definite limitations – limitations that stem for the most part from an avoidance of issues and problems in which fuzziness lies at the center rather than on the periphery. What has to be recognized is that in real-world settings such issues and problems are the rule rather than the exception."

---

[51] Extensions of prospect theory for multiple criteria outcomes are presented by Tversky and Kahnemann (1992), which they call as "cumulative prospect theory".
[52] Following are, for example, propositions containing fuzzy events: tomorrow will be a warm day; there will be a strong earthquake in the near future; the prices will stabilize in the long run; if it rains heavy tomorrow, my car will pass the emissions test.

On the other hand, Zadeh (1995: 275) claims that fuzzy logic offers "an effective methodology for exploiting the tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, and low solution cost. The key concept in this methodology is that of a linguistic variable – that is, a variable whose values are words rather than numbers (Zadeh 1973). The concept of a linguistic variable is the point of departure for the development of the calculus of fuzzy if-then rules." Recently, fuzzy decision theory has gained wider popularity among decision theorists. From a meta-decision theoretical perspective, however, fuzzy theory is also built on certain foundational assumptions that leave unanswered some of the meta-decision problems raised earlier in this chapter. Fuzzy decision theory, for example, allows the measurement of outcomes in terms of fuzzy quantifiers, but it does not answer "quantifiers of what values/nouns".

The meta-decision question of which values should be used to measure the outcome functions remains an elusive question both for the fuzzy as well as probabilistic descriptive decision theorists. Most of the probabilistic descriptive decision theorists have actually used very degenerate versions of lotteries (i.e. outcomes are strictly measured in monetary terms of costs and benefits). The values that cannot be monetized result in distorting reduction of the underlying non-linear utility functions into simple linear utility functions. Even the apparently non-linear utility functions have to resolve to some underlying weighting mechanism to convert the incommensurate values into common value measure, before it can be hypothesized that the utility function is non-linear as a function of that pre-weighted common value measure. Section 3.3 reviews meta-decision problems in normative decision theories.

3.3: The expected value hypothesis and normative decision theory

Hwang and Yoon (1981) describe twelve most widely applied normative MCDM decision algorithms, many of which employ different methodologies to define A, z, w_q and the decision rule. All of the 12 decision algorithms assume exogenous determination of value and alternative sets that are mostly based on the preferences of the decision makers. But preferences of the decision makers are intransitive, inconsistent, spontaneous, context-sensitive and dynamic, as I have shown through the review of descriptive decision theory in section 3.2. The exogenous determination of alternative and value sets is a vital limitation of normative decision algorithms. Next I discuss each

decision algorithm's methodology of determining the weights w_q and their respective decision rule to determine the solutions, i.e. assigning rankings (i.e. strict or partial order) over the set of alternative paths A.

The dominant decision algorithm requires the determination of dominant and non-dominant alternative paths, which in fact is a subjective preference method to assign weights to multiple decision criteria. The decision rule is to choose a subset of non-dominated alternatives from the set of A. Due to non-transitive group preferences; it sometimes happens that this decision algorithm finds neither entirely dominated nor non-dominated alternatives. Neither the maximin nor maximax decision algorithms can be applied unless the multiple decision criteria have commensurate units of value, which is rarely the case in complex environmental decision problems.

There are methodologies that convert the incommensurate units of value into commensurate units by establishing the relative ratios, which in itself pre-supposes a methodology to assign weights to multiple criteria, since more than one denominator can potentially be chosen to estimate the relative ratios. Both conjunctive and disjunctive decision algorithms require determination of minimum satisfactory cut-points for each of the policy alternatives. Alternatives that meet these minimum satisfactory requirements of multiple decision criteria are called "satisficing" alternatives in the previous literature (Simon 1960; Simon 1977; Simon 1982). Conjunctive and disjunctive methods are useful in limited situations where satisficing alternatives are determinable. However, in complex decision problems, it is not easy to determine the satisfactory cut-points. If the cut-points are set too high, the algorithm would not choose any satisficing alternative, or if the cut-points are set too low, the algorithm would end up choosing all the alternatives as satisficing.

Choosing cut-points is thus like determining the weights to be assigned to the multiple decision criteria in conjunctive and disjunctive decision algorithms. Both lexicographic and elimination-by-aspect decision algorithms assume *a priori* that decision makers can arbitrarily assign weights to the multiple decision criteria by rank ordering them from the most important to the least important. This rank ordering is, however, not easy to establish in complex situations because some stakeholders may emphasize efficiency criteria and attach zero weight to fairness, or vice versa. Further, it is precisely this *a priori* allocation of weights that I perceive to be the root cause of present confusion in environmental policy decision problems. In the case of simple

additive weighting and weighted product decision algorithms, in which both decision algorithms assume that the weights are assigned exogenously, the issue of weights is left to the whim of the decision maker.

Furthermore, the decision algorithm of TOPSIS requires exogenous determination of positive and negative ideal values. So, in the process of assigning positive and negative ideal values, one decision maker may choose an alternative *i* as an optimal solution because *i* is closest to the set of her positive ideal values and farthest from the set of her negative ideal values [in terms of Euclidean space]. A conflicting decision maker, on the other hand, may reject the same alternative *i* as an optimal solution because *i* is farthest from his set of positive ideal values and closest to his set of negative ideal values. The important issue in applying TOPSIS to collective environmental decision making problems is that the assignment of positive or negative ideal values cannot camouflage the assumption that these ideal values are actually euphemisms for assigning *a priori* weights to the multiple decision criteria.

The decision algorithm of ELECTRE, though highly sophisticated in other respects, also requires the exogenous determination of weights for multiple decision criteria. The ELECTRE method has another serious problem: that of confronting the empty Kernel, which is a situation in which none of the alternatives can outrank all of the other alternatives. Finally, the decision algorithm of analytical hierarchical process (AHP) explicitly recognizes the need to identify weights for the multiple decision criteria, and provides a useful technique: a 9-point intensity scale that compares the incommensurate multiple decision criteria. This method would, however, require the determination of one over-arching focus or objective of the decision maker, while I have argued that, in the case of complex environmental management decisions, one objective cannot be maximized because each objective competes with other worthy objectives. Assuming that the decision maker has found one over-arching objective, then AHP requires the determination of weights for the multiple-decision criteria through pair-wise binary comparisons among all possible permutations of criteria for each of the alternatives.

The analysis of the 7 descriptive and 12 normative decision algorithms shows that the assumption that it is possible to find algorithmic solutions has blocked most MCDM researchers from addressing truly complex environmental policy decision

problems because the real problem of meta-decisions is assumed to be taken care of through means that are exogenous to their models. This theoretical block, in my view, is pervasive in decision theory because the methodological assumptions for deciding about meta-decisions have not been critically analyzed. The emphasis has rather been on finding an algorithm that provides the best and most optimal decision. Complex environmental policy problems, as I explained before, cannot by definition have singular, optimized solutions because exogenous decisions on meta-choices foreclose the real issues and reduce the decision problem to mere application of pre-defined algorithmic decision rules, while in actual policy contexts, these meta-choices make a real difference in each stage of evaluating the decisions.

Dutta (1996) provides a survey of recent efforts by decision theorists to integrate Artificial Intelligence (AI) and optimization (OPT) models for programming the meta-decisions and finding a meta-decision algorithm. Dutta (1996: 224-6) concludes that integration of AI and optimization models is still facing a paradigmatic crisis due to the following unresolved issues: (a) Aritificial intelligence representations, such as rule bases and frames often use list structures that are very different from the arrays and matrices used by optimization models. The consequence is that programming languages for optimization models are fundamentally incompatible to AI languages. (b) A second barrier to AI/OPT integration is the sheer complexity of information that may need to be exchanged for seamless integration.   Dutta (1996), however, remains optimistic that integration of AI and optimization models will occur once we overcome these barriers.

Hanne (2001) is an excellent resource for understanding the meta-decision problem in MCDM, though he binds the meta-decision problem to just the choice of a suitable MCDM methodology. Hanne (2001: 25-31) reviews the following four approaches in previous MCDM literature that have been used to resolve the meta-decision problem of method selection for a decision problem: (a) the suitability of a decision model for a type of decision problem; (b) meta-criteria based on solution concepts; (c) meta-criteria oriented towards implementation of the proposed solution to decision problems; and (d) meta-criteria based on the specific decision situation. Hanne (2001) treats the meta-decision problem as a problem of method design: First, he shows that the MCDM decision algorithms are basically parameter optimization problems, and

these decision algorithms are not capable of making meta-choices. Second, he shows that all of the MCDM decision algorithms share the ontological commitment of finding efficient solutions and maintaining partial order in formal mathematical and logical terms. Third, he proposes that meta-decision problems are solvable by constructing new methodological designs for MCDM problems, such as neural networks and evolutionary learning algorithms, which can act as meta-algorithms that can find optimal solutions through constantly updating the parameter values of the selected MCDM methods. The updating of parametric values is carried out by the learning mechanisms incorporated in the meta-algorithms such as neural networks and evolutionary models.

This brief survey shows that MCDM researchers still cherish the hope of finding a meta-decision algorithm that will find optimal solutions to multiple criteria decision problems. My contention is that MCDM researchers will not be able to resolve the complex decision problems, especially the meta-decision problems, unless they give up the ontological commitment of finding singularly best and optimal solutions through decision algorithms. Furthermore, MCDM researchers should also accept that decisions -- both descriptive and prescriptive -- are part of larger continuous decision processes, which are riddled with uncertainty and ignorance. In section 4.1, I show that air quality management decision problems, involving potential emission reductions from high-emitting vehicles, are complex in nature and require extremely difficult decisions on meta-choices, such as choices of A, z, w and the decision rule.

A review of normative (section 3.3) and descriptive (section 3.2) decision theories opens up a Pandora's box of unanswered questions; especially the meta-decision problems raised in section 3.1 appear to remain unanswered. At the same time, it is only at the meta-decision level that both descriptive and normative decision theories can be reconciled and real world decisions can be researched. At one level, the researchers can aim to describe the real world decision behaviors in specific contexts; while at the other level, the researchers can undertake normative analysis to see which values are used to set up the context of our decisions. In the next section 3.4, I show from a meta-decision theoretical perspective that decision making in environmental policy is confronted with the question: which values are/should be chosen to measure the impact of the decision behavior of individual agents on the outcomes of policy actions?

3.4: The logic and methodology of meta-decision models in environmental policy

In a Meta-Decision Model (MDM), environmental policy decisions are modeled at two interactive levels: At the level of action, descriptive analysis is undertaken to ascertain the current state of the world, such as existing policies, and the outcomes ensuing from current policies/decisions. At the meta-level of reflection, normative analysis is employed to determine the socially desirable values by which outcomes of (current and future) policy actions are measured.

MDMs explicitly aim to resolve meta-decision problems. In section 3.1, I have defined four critical meta-decision problems that are shared by 7 descriptive and 12 normative decision algorithms: choice of value/criteria set, choice of alternative set, choice of weights for the values and choice of the decision rule. The meta-decision models do not treat the meta-decision problems as exogenous to the policy evaluation system; rather these choices are treated as endogenous to the policy system. Both decision analysts and decision makers cannot move further in their analysis without making meta-choices. Instead of hiding these choices in the mystical shrouds of programming languages employed in decision algorithms, MDMs aim at focusing on meta-choice decision problems.

The focus on meta-decision problems however comes at an extreme cost: The decision scientists will perhaps, at least in the short run, not be able to construct a universal and non-regressive meta-decision algorithm. The cost is that decision sciences will have to do away with the notion of programming every unprogrammed decision, or in other words, the price is the abandonment of the decision algorithmic approach. The proposed meta-decision models are thus not written in the logical terms of syntactical and semantical rules. The meta-choice decision problems, by their very definition, are concerned with the *choice* of a syntactical and semantic system for environmental evaluation that is sensitive to the context in question and to appropriate space-time horizons. The meta-choices have to be written and communicated in ordinary language, which is not as determinate as syntactic and semantic systems; rather the pragmatics of language play a very dominant role in the construction and understanding of meaningful statements in environmental policy discourse.

Meta-decision problems are tied up with natural languages employed by human decision agents in societal communication processes, which means that environmental policy discourse is indispensably carried out in multiple languages/discourses. Multiple

languages evolve under various natural and conventional contexts, in which shared environmental discourse is carried out. **Proposition 3.1** states that the outcomes described/prescribed in environmental policy discourses are functions of the natural and conventional contexts of the discussants/decision makers. The meta-decision models in environmental policy analysis are thus context sensitive and they cannot be conceived or understood independent of the context. In section 3.4.1, I explain in more detail the context sensitivity of the outcomes, as they are measured/conceptualized in meta-decision models on multiple value-dimensions.

Proposition 3.2 states that the outcomes of environmental policy actions cannot be characterized in absolutist terms, valid for once and always; rather outcomes occur as continuous processes, for which no fixed spatio-temporal boundaries can be drawn. Policy scientists, however, need to draw "artificial" spatio-temporal boundaries around any environmental policy decision problem to measure the outcomes under different states of the world on multiple value-dimensions. Section 3.4.2 elaborates the process-orientation of the outcomes which is an important ingredient of the meta-decision models.

Proposition 3.3 states that the environmental policies cannot be treated as fixed on any *a priori* knowledge grounds. The policy actions are rather treated as experimental in nature and open to change as context and power relations change in human societies. The meta-decision models are thus adaptive and experimental, which I explain in detail in section 3.4.3. Section 3.4.4 elaborates the broader/generalized methodology of the meta-decision models.

3.4.1: Context sensitivity

It turns out that one can identify at least three broad types of contextual features of any multiple-valued outcome (X) of an environmental policy decision. Let us call them conventional contexts (C), natural contexts (N) and technological contexts (T). Formally:

Equation 3.9: X = f (C, N, T)

Conventional contexts include the type of decision context imposed by the social aspects of the choice situation, such as the nature of institutions in a place, its governance structures and laws, and values of the society. Empirically, I model the conventional context to be a sub-function of decision behaviors/actions (A). Formally:

Equation 3.10: C = g (A)

Natural context includes the description of state of physical/natural features of the environment in question. Empirically, natural context is described through physical/natural parameters (Q) of the policy system/question. Formally:

Equation 3.11: N = h (Q)

Technological context indicates the specific technological regime (R) that exist in the spatio-temporal horizon of the environmental policy decision problem. For example, the technological regime of emission control systems and fuel inputs for vehicles represents the technological context of air quality management decisions that concern vehicular emissions. Formally:

Equation 3.12: T = i(R)

I define the outcome of a decision as "context-sensitive", if the decision analyst and/or decision maker includes the conventional, natural and technological contexts of a decision in evaluating alternative courses of actions. Formally:

Equation 3.13: X = f [C(g(A)), N (h(Q)), T (i(R))]

Conversely, I define the outcome of a decision as context-free if the decision analyst and/or decision maker uses a decision making algorithm (such as the ones presented in sections 3.2 and 3.3) that does not take into account conventional, natural and technological contexts of the decision situations.

3.4.2: Process-orientation

The outcomes of policy decisions occur at multiple spatio-temporal scales in a continuous process, which cannot be absolutely quantified. Any horizon of an environmental policy decision problem can only be defined once the spatio-temporal boundaries of a decision problem are drawn. Outcomes of continuous and context-sensitive decision processes are thus observed in specific slices of space (s) and time (t). Formally:

Equation 3.14: $X_{st} = f [C(g(A)), N (h(Q)), T (i(R))]_{st}$

3.4.3: Adaptive and experimental

Environmental policies are treated as experimental in nature, and can therefore be changed in subsequent time periods as new information is made available to the policy makers about the outcomes of policy decisions in previous time periods. Environmental policies are thus treated as adaptive. I presented the concept of adaptive mechanism/policy designs in section 2.4.

3.4.4: The methodology:

Essentially, meta-decision models aid meta-choice decisions by applying meta-criteria heuristics. I accept the considerable limitation that the choice of meta-criteria heuristics is itself open to change as meta-meta-criteria evolve in human societies, as well as in their languages and discourses. Here I want to emphasize the role of practical reasoning and the logic of pragmatism. Any logical decision system is confronted with the possibility of an infinite regress of meta-choices. It is, however, practical reason that guides us to eschew the possibility of infinite regress -- pragmatism leads us to base our decisions on the basis of real world outcomes of actions as observed empirically by a researcher at the level of action. At the same time, for heuristic purposes, a meta-level of reflection is introduced in MDMs, at which normative analysis is carried out. On pragmatic grounds, all meta-meta-level choices can be considered as driving the normative analysis at meta-level of reflection. A detailed discussion of meta-meta-level [and higher level] choices is left as an area for future research in relation to hierarchical systems theory. In this dissertation, due to the pragmatic demands of environmental policy decisions, I limit the discussion to meta-choices and their relationship with meta-criteria heuristics.

Meta-criteria heuristics act as principle determinants for temporarily resolving meta-decision problems. The meta-decision problem of value-ambiguity, for example, is explicitly explored at the outset by the policy designer. In the case of environmental policy decisions, the foremost value is perhaps efficient/effective reduction of contaminants/pollutants from our environments. Outcomes in MDMs will thus invariably involve environmental pollution/resources as one scale/dimension of measurement. Most of the environmental regulatory mechanisms are designed to attain the outcomes on this value scale. This is one important part of descriptive decision analysis at the level of action in MDMs, but it is not the whole story. MDMs also aim at evaluating the outcomes of environmental policy decisions on other value scales/dimensions that are considered important by the civilized society. Which other values should thus be included to measure the outcomes, however, always remains an outstanding and iterative feature of MDMs.

MDMs thus recommend strong collaboration between expert-based decision-aid systems and participatory/collaborative models of decision making because it is only through participation of large segments of affected decision makers that experts can

correctly identify the values on which the outcomes of policy actions are measured at the level of action in MDMs. For demonstration of MDM application at the level of action in real-world policy situations, I use two non-commensurate values – effective emission reductions and fairness – to measure the outcomes of IM program/policy intervention in the Atlanta airshed between 1997 and 2001. The generalized case of n-valued outcomes of environmental policy interventions is discussed in chapter 7.

At the meta-level of reflection, the policy designer compares the outcomes measured at the level of action with the outcomes that are deemed normatively desirable within the space-time horizon of environmental policy decisions. At this level, once again, meta-decision problems are resolved through iterative experimentation and collaboration between expert and lay decision-makers. The normative analysis at meta-level of reflection results in policy prescriptions/recommendations that aim at getting "there" from "here" given all the uncertainty, ignorance and incomplete information. The normative analysis at the level of reflection for Atlanta's airshed—in value terms of attaining outcomes that balance/maximize effective vehicular emission reductions and fairer distribution of program/policy costs—is presented in chapter 7 in the light of descriptive results, which are presented in chapter 6.

Next, in chapter 4, I explain the background of IM program/policy intervention in the Atlanta airshed, review literature on previous evaluation studies that concern effective vehicular emission reductions as well as fairness outcomes of IM programs in USA, in general, and in Atlanta, in particular. The research design for operationalizing MDM application in Atlanta airshed at both levels of action and reflection is presented in chapter 5.

CHAPTER 4

THE REGULATORY MECHANISM OF VEHICLE INSPECTION AND MAINTENANCE (IM) PROGRAMS: A CASE STUDY OF THE ATLANTA AIRSHED

4.1 Vehicular tail-pipe emissions and travel patterns: the raison d'être of vehicle inspection and maintenance (IM) programs

While gasoline-powered automobiles increased exponentially in the twentieth century as the modal choice of travelers, concerns about the impact of automobile tail-pipe[53] emissions on the air quality have also raised serious environmental challenges. The data from American Automobile Manufacturers Association shows that worldwide automobile stocks increased eight-fold from 75 million in 1950 to 600 million in 1992. United States alone experienced a four-fold rise of motor vehicle stocks from 50 million to 200 million vehicles between 1950 and 1992. One-third of the total world motor vehicle stocks in 1992 were registered in the United States. The 2001 estimate of motor vehicle stocks stood at staggering 235 million in USA, of which about 7 million were registered in the state of Georgia.[54]

Corresponding to the exponential rise in the stocks of motor vehicles, the flow of carbon monoxide (CO), oxides of nitrogen (NOx) and hydrocarbon (HC) tail-pipe emissions from on-road automobiles increased exponentially between 1950 and 1975 but decreased since 1975. Based on an EPA simulation model (2000), Figures 4.1 to 4.3 show respectively the trends in CO, NOx and HC emissions flows from on-road automobiles between 1940 and 1998 in the USA. These figures also show respectively the trends in CO, NOx and HC emissions flows from other sources such as fuel combustion, industrial processing, and non-road sources in the USA.

---

[53] In addition to *tail-pipe* emissions, vehicles also emit *evaporative* emissions. Evaporative emissions are not the focus of this study, though they constitute an extremely important part of over-all environmental policy to control vehicular emissions.
[54] Source: vehicle registration data at www.transtats.bts.gov
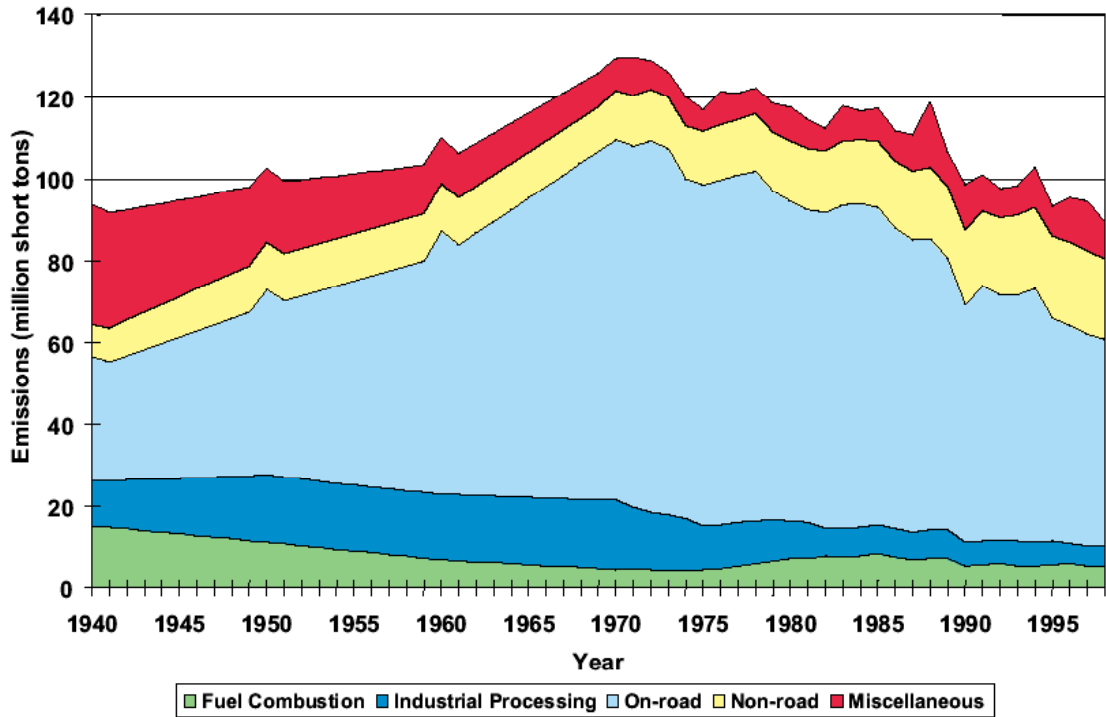
Note: Some fluctuations in the years before 1970 are the result of different methodologies

Figure 4.1: Simulated trend of Carbon Monoxide (CO) emissions from 1940 to 1998 in the USA. Source EPA (2000).
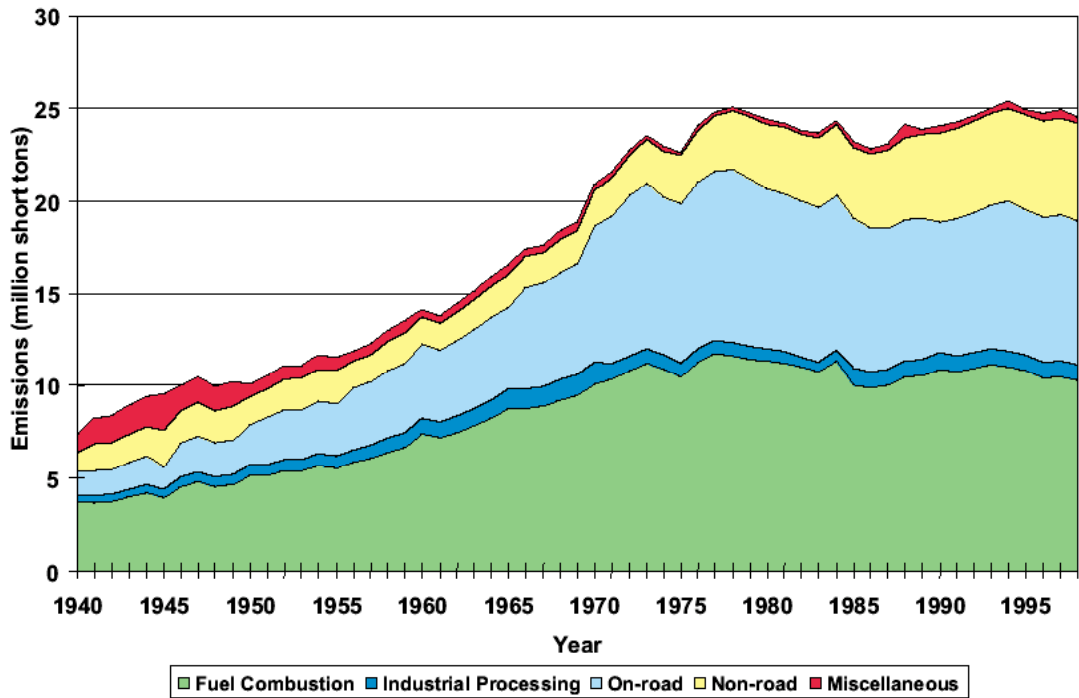
Note: Some fluctuations in the years before 1970 are the result of different methodologies

Figure 4.2: Simulated trend of Oxides of Nitrogen (NOx) emissions from 1940 to 1998 in the USA. Source EPA (2000).
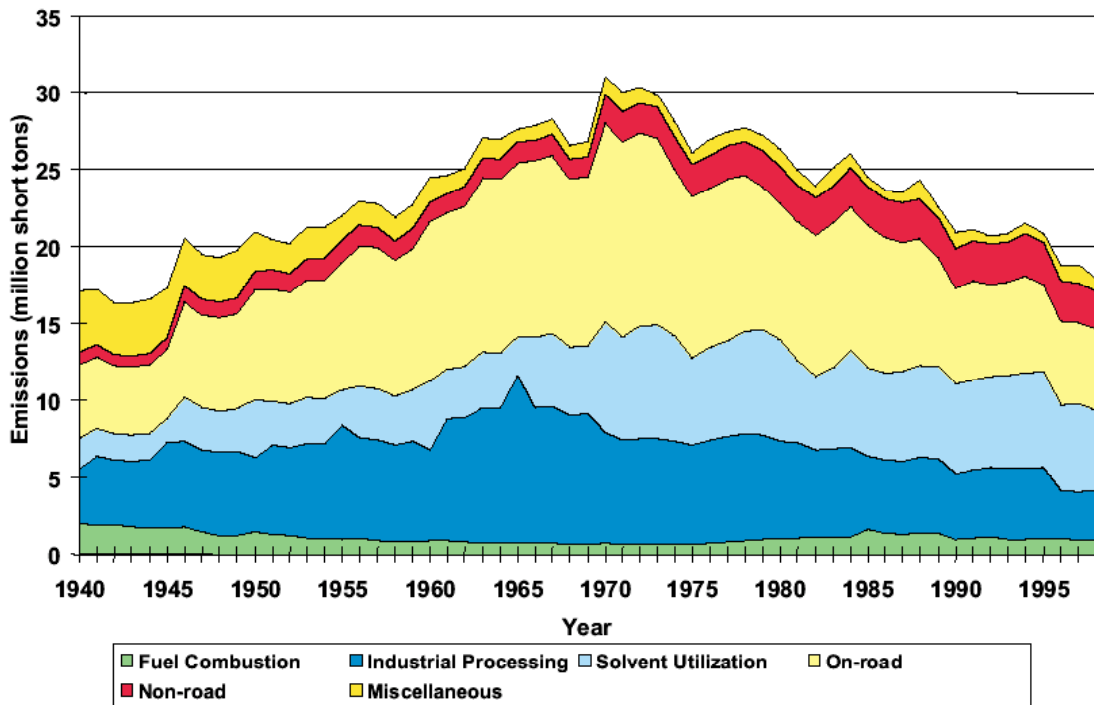
Figure 4.3: Simulated trend of Volatile Organic Compounds emissions from 1940 to 1998 in the USA. Source EPA (2000).
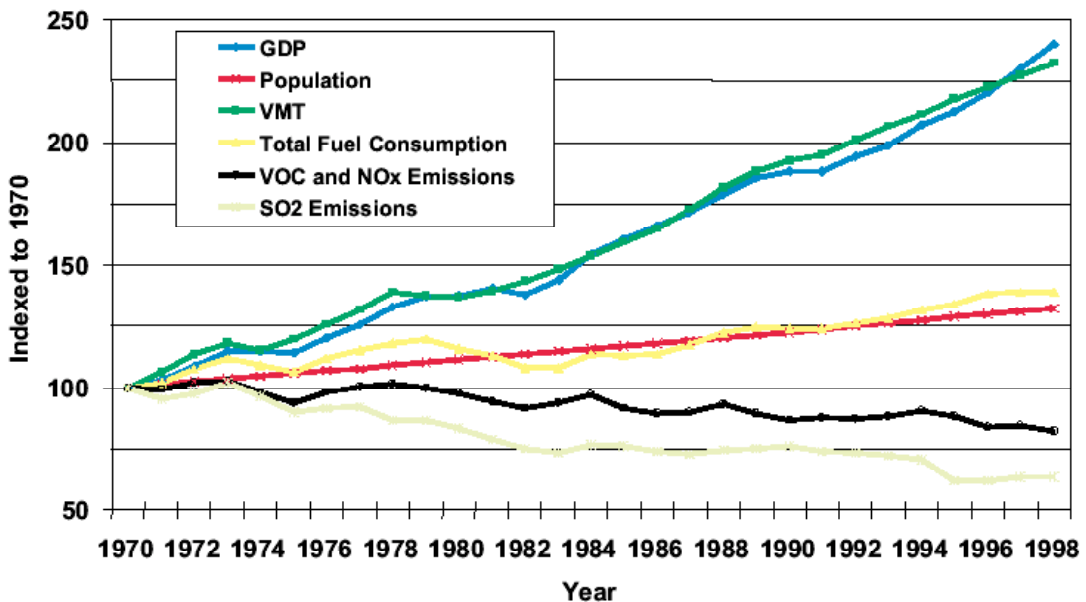
Figure 4.4: Simulated trend in gross domestic product (GDP), population, vehicle miles traveled (VMT), total fuel consumption, VOC and NOx emissions, and SO₂ emissions in the USA between 1970 and 1998. Source EPA (2000).

78

One noticeable feature in figures 4.1 to 4.3 is that the exponential trend in the on-road automobile emissions tapered off after 1975. CO emissions flows decreased from more than 80 million tones per year in 1975 to less than 50 million tones per year in 1998, where as NOx and HC emissions flows remained almost constant during this period respectively at less than 10 and 5 million tones per year.

The tapering off trend of vehicular tail-pipe emissions flows since 1975 is mostly attributed to various emission control technological innovations that have been introduced in automobiles since the early 1970s. The emissions control hardware on automobiles has changed over time to reflect changing regulatory emissions standards as well as changes in vehicle design, fuel efficiency standards and technological capabilities (NRC 2001: 46). Emission control systems on vehicles are grouped into three categories: engine, evaporative, and diagnostics. This dissertation is focused on engine emission control systems,[55] which experienced the following three major stages of technological innovations in chronological order: (1) Engine adjustments were introduced between 1968 and 1974. Primary engine adjustments consisted of modifications to mixture[56] strength and spark timing; (2) Oxidizing catalysts were introduced between 1975 and 1980. Lean mixtures and two-way oxidation catalysts were used for HC and CO controls. The technology of Exhaust Gas Recirculation (EGR) was also introduced during this period to control NOx. (3) Closed-Loop combustion controls (CLL) and Three-way catalysts (TWC) have been introduced in automobiles since 1981. CLL allows precise mixture configuration, while TWC control tail-pipe emissions of HC, CO, and NOx. The technological parameters of emission-control systems on automobiles, briefly, indicate if a vehicle is fitted with Oxidation (two-way) catalyst (Oxy), Three Way Catalyst (TWC), Positive Crankcase Ventilation System (PCV), Exhaust Gas Recirculation (EGR), Closed Loop Combustion Control (CLL), Air Injection Reactor system (AIR) and Thermostatic Air Cleaner (TAC). More details about these emission control technological systems can be found in NRC (2001:48-52).

---

[55] More detail about evaporative and diagnostic emission control systems can be found in NRC (2001: chapter 4).
[56] Mixture is technically air/fuel ratio, which is the ratio by weight of air to gasoline entering intake in a gasoline engine. The ideal ratio for complete combustion is 14.7 parts of air to 1 part fuel. Air/fuel ratio less than 14.7 are termed "rich mixtures" and contain excess fuel for combustion, while air/fuel ratios greater than 14.7 are termed "lean mixtures" and contain more air than is required for complete combustion (NRC 2001: 48).

It has been argued that the automobile manufacturers introduced these technological innovations after they faced stringent regulatory laws mandated under the US Clean Air Act 1970 and its amendments in 1977 and 1990 (EPA 2000; NRC 2001). Total HC and NO emissions are somewhat constant[57] because massive declines in per-vehicle emissions (following technological innovations) have been largely offset by rapidly rising VMT. Figure 4.4 compares the VMT growth trend in the USA with other major macro-indicators between 1970 and 1998, such as gross domestic product (GDP), population, total fuel consumption, volatile organic compounds (VOC) and NOx emissions. This figure shows that both VMT and GDP have more than doubled between 1970 and 1998, while the VOC and NOx mass emission rates decreased by about 30% in the same period. The trends in population and fuel consumption, both of which were about 1.3 times higher in 1998 than their 1970 levels, also overlap. Figure 4.4 is based on an EPA (2000) simulation model, which unfortunately does not indicate the expected error rate and gross uncertainty associated with estimating the VMT and actual emissions from multiple anthropogenic and non-anthropogenic sources.

Large scientific uncertainty is also associated with the potential impact of the on-road vehicle tail-pipe emissions on human, animal and plant environments. Previous studies have attributed increased asthma among children due to secondary pollutants, such as ozone, which are formed after the primary pollutants, such as NOx and HCs, from motor vehicles react in the atmosphere during high-temperatures (Edwards, Walters et al. 1994; Friedman, Powell et al. 2001; Livingstone, Shaddick et al. 1996; Wjst, Reitmeir et al. 1993). Following research, in contrast, focuses on evaluating various precautionary policies that can proactively reduce the primary pollutants – CO, HC and NOx – that are emitted from the tail pipes of on-road vehicles.

The search for appropriate policy actions to proactively reduce tail-pipe vehicular emissions is however confronted with the meta-decision problem of bounding the set of policy alternatives that was explained in chapter 3. Figure 4.5 shows various policy alternatives – including IM programs -- that can possibly be employed at multiple spatio-temporal scales of policy outcome horizons to reduce tail-pipe emissions from on-road vehicles.

---

[57] The constant rate since 1975 is estimated at 10 million tones per year for NOx and 5 million tones per year for VOCs, as it is shown in figures 4.2 and 4.3.
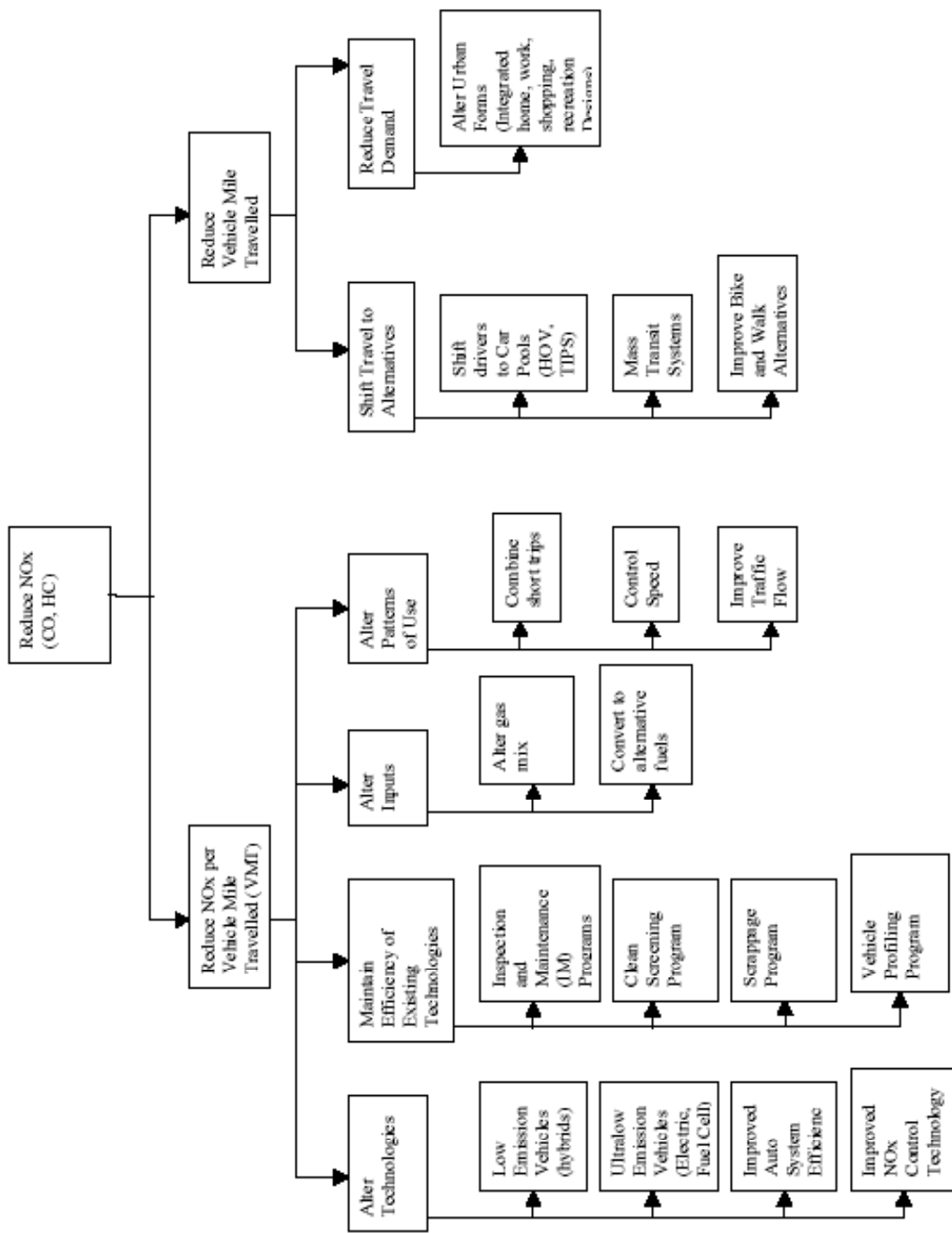
Figure 4.5: The wicked problem of emission reduction strategies for on-road vehicle sources

The evaluation of an IM program, in particular its impact on high-emitting vehicles, is a complex policy design problem because no particular decision rule can be applied to address the meta-decision problem of bounding the set of policy alternatives.

First, formulating the decision problem and clearly defining the set of alternatives involves complex choices because reductions in CO, NOx and hydrocarbon (HC) vehicular emissions due to IM programs are not separable from other causal factors and policy interventions that affect the emissions of these pollutants. This is illustrated in figure 4.5, which shows that the CO, NOx and HC tail-pipe emissions from on-road vehicles can be reduced either by reducing these emissions per vehicle miles traveled (VMT) or by reducing the VMT itself.

The emissions per VMT can be reduced by (1) altering the technologies (such as introduction of low, ultra-low and zero emission systems on vehicles), (2) changing the inputs (such as altering the gasoline mixes and converting to alternative fuels), (3) changing the patterns of vehicle use (such as combining short trips, controlling speed and improving the traffic flow), and (4) maintaining the efficiency of on-board emission control technologies (such as IM programs, clean screening and vehicle profiling programs, scrappage programs and automobile manufacturer insurance programs).[58]

The VMT itself can also be reduced by both shifting travel to environment friendly alternatives (such as shifting drivers to car pools, mass transit systems and improving biking and walking alternatives) as well as reducing travel demand through long-term regional planning (such as altering landscape forms by using integrated home, work, shopping and recreation designs). The IM program, the policy intervention to be evaluated, is essentially pursued under the strategy of maintaining the efficiency of emission control technologies mounted on on-road vehicles, which falls under the higher order objective of reducing emissions per VMT (or also emissions per unit of fuel consumption). The policy alternatives to IM programs are nested within each other and have impacts at multiple spatio-temporal scales. Vehicular technologies are changing at

---

[58] It is not necessary that IM, clean screening, vehicle profiling, scrappage and insurance programs only affect the higher order objective of keeping the on-board emission control technologies efficient, rather it is possible that they also affect the other higher order objectives, such as changing the fuel inputs and patterns of vehicle use. This further adds to the complexity of the meta-decision problem of choosing the set of alternative actions by policy makers.

a much more rapid temporal scale than the transportation infrastructure. The set of policy alternatives to evaluate the IM program can either be bounded by the alternatives that can be designed to maintain the efficiency of emission control systems in changing vehicle technologies, or it can be unbounded to include all the policy alternatives listed in terminal nodes of Figure 4.5, which is not an exhaustive list. The complex problem is where to set the boundaries and how to bound the set of alternatives. This will require decisions at the meta-level.

While it would be interesting to compare and explore the integrative impact of all of the nested strategies outlined in figure 4.5 for possibly reducing the on-road vehicular tail-pipe emissions, the following research narrowly focuses on evaluating the decision behaviors of high-emitting vehicle owners in the *existing* IM program in the Atlanta airshed.

In section 4.2, I present brief description of IM programs as mandated by 1990 CAAA and compare IM programs' design parameters across the states. Section 4.3 presents a brief history of IM program in the Atlanta airshed as well as description of IM program rules during the study period 1997 to 2001. In section 4.4, I review prior research that—in particular by using remote sensing data -- evaluated the vehicular tail-pipe emission reduction effects of IM programs. In section 4.5, the decision behavioral research studies that have been carried out in the context of IM programs are reviewed. In section 4.6, I present an argument that multiple decision criteria evaluation of IM programs is needed, and show how can this be carried out by operationalizing Meta-decision Models (MDMs), the task of this dissertation.

4.2 The 1990 Clean Air Act Amendments and IM programs: A regulatory environmental discourse

The 1970 Clean Air Act (CAA) was the first legislation that gave states the option to implement IM programs and delegated responsibility for program oversight and guidance to the U.S. Environmental Protection Agency. IM programs were made mandatory under the 1977 CAA Amendments for states which were persistently not complying with federal air quality standards. EPA's first guidelines for IM programs provided information about the minimum emission reductions required for such programs, as well as implementation requirements and timeframes (EPA 1978). It is noticeable that the general and to some extent vague nature of EPA's 1978 guidance

document resulted in IM programs that vary significantly in IM design and enforcement parameters from state to state, as shown in table 4.1.

Table 4.1: a comparison of IM program elements across the various states in the USA (adapted from NRC 2001: 41-42)

IM program area	IM Net-work type	Test type	Cutpoint[a]	Visual checks	Frequency	Vehicle types	Model years
Alaska	Test & repair	2- speed idle	220/0.5	Catalyst, air pump, EGR, PCV, evap. disable	biennial	LDGVs LDGTs	Anchorage 1968+ Fairbanks 1975+
Arizona (Phoenix)	Test only	81+: IM147 <81: idle and cruise	2/12/3 220/1.2	Catalyst, air pump, PCV, evap. disable	annual	all	1967+ <5 exempt
Arizona (Tucson)	Test only	80+: idle and cruise <80: idle	220/1.2	Catalyst, air pump	biennial	LDGVs LDGTs	1974+ <4 exempt
California (basic)	Test & repair	2-speed idle	220/1.2	Catalyst, air pump, EGR, fuel inlet	biennial	LDGVs LDGTs HDGVs	1974+ <4 exempt
California (enhanced)	Hybrid	ASM	120/1.0	Catalyst, air pump, EGR, PCV, evap. disable	biennial	LDGVs LDGTs HDGVs	1974+ <4 exempt
Colorado (Denver and Boulder)	Test only	82+ IM240 <82: idle OBD: MIL check	5/25/8 300/3.0	O_2 sensor, catalyst, air pump, fuel inlet	82+: biennial <82: annual	LDGVs LDGTs HDGVs	All except <4 exempt
Colorado (Colorado springs, Greeley, and Fort Collins)	Test & repair	81+: 2-speed idle <81: idle OBD: mil check	400/1.5	O_2 sensor, catalyst, air pump, fuel inlet	82+: biennial <82: annual	LDGVs LDGTs HDGVs	All except <4 exempt
Delaware	Test only	81+: 2-speed idle	220/1.2	Catalyst, fuel inlet	biennial	LDGVs LDGTs	1968+
Georgia	Hybrid	2-speed idle for <5 years old, ASM for older	220/1.2	Catalyst, gas cap	Biennial till 2000 and annual since 2001	LDGVs LDGTs	1975+ <2 exempt till 2000

[a]Cut points are for HC in ppm and CO in percent for ASM and idle test, and for HC, CO, and NOx in grams per mile for IM240 and IM147 tests.

Table 4.1 shows major design parameters of selected IM programs in Alaska, Arizona, California, Colorado and Georgia. Important regulatory design parameters of IM programs include decisions from the state-level regulators on the following eight important issues (which are shown for nine different IM programs, including Atlanta, GA, in table 4.2): (1) What should be the IM program's network type (centralized, decentralized or hybrid)?[59] (2) What should be the IM test type (Idle, ASM, IM 240, IM 147)?[60] (3) What should be the emission cut-points to separate out high-emitters from normal emitters? (4) What kind of visual checks and (5) evaporative tests should be undertaken? (6) What should be the frequency of IM testing? (7) Which vehicle types and (8) vehicle model years should appear in the IM test?

The design parameter of the IM network type – i.e. whether emissions testing should be conducted by centralized, decentralized or hybrid networks of testing stations – was debated extensively during the 1980s. In particular, EPA attributed the IM program's lack of effectiveness during the 1980s to decentralized network types and cited improper testing and poor quality control as a leading cause of ineffectiveness.

---

[59] A centralized network consists of a relatively small number (relative to a decentralized network) of stations that perform only emissions tests. Vehicles that fail the emissions must be repaired elsewhere. This network typically is operated by a government entity or by a contractor with government administration (NRC 2001: 58). A decentralized testing network consists of a larger number of low-volume stations that do both emissions testing and vehicle repairs. This type of network links testing to the repair process and is operated by private sector stations (NRC 2001: 59). A hybrid network is one that incorporates elements of both decentralized and centralized programs. One hybrid type, for example, may incorporate both high volume centralized test-only stations and low volume decentralized repair-and-retest stations; while another hybrid type may incorporate high-volume decentralized test-only stations and low volume centralized repair-and-retest stations (NRC 2001:60).

[60] There are two basic kinds of emissions tests: (1) Mass emissions tests include following: (a) the Federal Test Procedure (FTP) which measure the tail-pipe and evaporative emissions from new vehicles over the Urban Dynamometer Driving Schedule, which attempts to simulate an urban driving cycle. Automobile manufacturers are required by EPA to pass FTP for prototypes of vehicle models before being sold for the first time. (b) the IM 240 test is a loaded-mode transient dynamometer test, which measures the mass of emissions collected over a 240-second, 2-mile driving cycle that corresponds to the first 240 seconds of FTP. In addition, there are shortened versions of IM 240 test, such as BAR-31 (first 31 seconds), IM 93 (first 93 seconds) and IM 147 (final 147 seconds of IM240). (2) Concentration tests include following: (a) the Idle test is a steady-state unloaded test that uses a tailpipe probe to measure the concentrations of CO, HC and CO_2 in exhaust emissions from idling vehicles. The high idle test is measured at an engine speed of 2500 rpm, while the low idle test is measured at lower engine speeds. Idle tests do not measure NOx because unloaded vehicles have very low NOx concentrations. (b) ASM series of loaded-mode steady-state emissions tests measure exhaust concentrations from motor vehicles operated on a dynamometer. ASM 5015 test measures emissions at 50% of the maximum load conditions at a speed of 15 mph. ASM 2525 measure emissions at 25% of the maximum load conditions at a speed of 25 mph.

EPA believed that improper testing sometimes stemmed from an inherent conflict of interest in test-and-repair programs; emissions inspectors might be tempted to falsely pass a regular customer's vehicle or a vehicle that did not pass after repairs. Decentralized test-and-repair networks also have a greater number of geographically dispersed test stations that are operated independently of one another. As a result, EPA asserted, it was more difficult for administering agencies to ensure that test technicians were properly trained and that tests were competently and honestly performed. Furthermore, improved emission testing technologies, as well as the introduction/planning of newer tail-pipe emission control technologies led EPA to advise congress to revise IM related laws of the CAAA 1977 in the CAAA 1990.

The US Congress approved more stringent requirements for IM programs in the 1990 CAAA (Title I §182). The 1990 CAAA defines two IM program types, *basic* and *enhanced*. Basic IM programs apply to *moderate* and *marginal* ozone non-attainment[61] areas. Enhanced programs apply to *serious*, *severe* and *extreme*[62] ozone non-attainment areas with urbanized populations of 200,000 or more and to all metropolitan statistical areas with a population of 100,000 or more in the Northeast Ozone Transport Region. Enhanced IM program areas must use improved test technologies and test procedures; conduct centralized testing, unless the state demonstrates that decentralized testing is equally effective; inspect cars annually, unless a state demonstrates that less frequent testing is equally effective[63]; and deny vehicle registration to motorists who fail to comply with inspection requirements (Title I §182c3C).

---

[61] The national ambient air quality standard (NAAQS) for Ozone is based on the expected number of days per year with a one hour concentration of 0.12 ppm (parts per million) or greater. For an area to achieve attainment the average number of days above the standard within that area must be equal to or less than one for three consecutive years. This means that if an ozone-monitoring site measures four days above standard in a year, that site will be in violation even if no readings above standard are measured during the next two years. The area in which that monitor is located is considered to be a non-attainment area.

[62] Five classifications of non-attainment for the one-hour ozone standard are specified in the 1990 Clean Air Act Amendments (CAAA) – Marginal, Moderate, Serious, Severe, and Extreme. The severity or magnitude of the exceedance is determined by the amount that the measurement is above 0.12 PPM.

[63] While the CAAA legislation emphasized annual testing, most enhanced IM programs conduct biennial inspections to defray higher inspection fees that result from more costly advanced testing technologies.

The 1990 CAAA enacted radical changes in the scope and stringency of IM programs. Mandated in the wake of persistent growth in VMT and chronic air pollution in the nation's largest metropolitan areas, 1990 CAAA requires *enhanced* IM programs that employ advanced testing technologies and procedures as a way to better ensure the operability of vehicle emission control systems. This law also requires biennial evaluation of enhanced IM programs and on-road measurement of inspected fleet emissions, but does not link together the two requirements (CAA Title I §182c3C; CAA Title I §182c3Bi; Title I§182c3Ci).

Table 4.2: Passenger-car exhaust gaseous emissions standards (all values in grams per mile except as noted) [adapted from NRC 2001: 27]

	50,000 miles			100,000 miles		
	HC	CO	NOx	NMHC[a]	CO	NOx
Model Year						
Precontrol[b]	10.6	84.0	4.1	--	--	--
1968-1969	275 ppm	1.5%	--	--	--	--
1970-1971	4.1	34.0	--	--	--	--
1972	3.4	39.0	--	--	--	--
1973	3.4	39.0	3.0	--	--	--
1975-1976	1.5	15.0	3.1	--	--	--
1977-1979	1.5	15.0	2.0	--	--	--
1980	0.41	7.0	2.0	--	--	--
Category						
Tier 0 (1981-93)	0.41	3.4	1.0	--	--	--
Tier 1 (beginning with model year 1994)	0.41 (0.25)[a]	3.4	0.4	0.31	4.2	0.6
NLEV (beginning with model year 1999)	--	--	--	0.09	4.2	0.3
Tier 2 – default set in 1990 CAAA (beginning with model year 2004)	--	--	--	0.125	1.7	0.2
Tier 2 – current proposed standards (beginning with model year 2004)	--	--	--	>0.09[c]	>4.2[c]	0.07

One important design parameter of IM programs concerns emission cut-points. It should be noted that IM program emission cut-points are always higher than the emissions standards that are set for automobile manufacturers. Table 4.2 (NRC 2001:27) shows passenger car exhaust gas emissions standards for various model

Passenger–car emissions standards
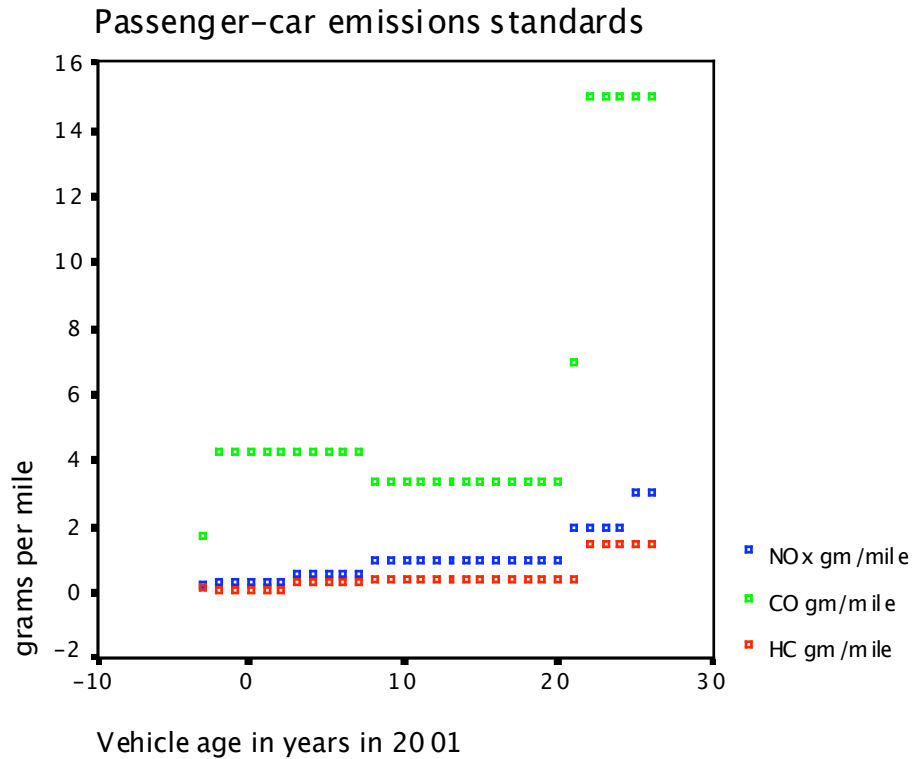
Figure 4.6: EPA-mandated passenger-car tail-pipe emissions standards required from manufacturers

years/ages and categories of vehicles that have been imposed by EPA/regulators on automobile manufacturers. It is noteworthy that as age of the vehicle decreases, the HC, CO and NOx standards become more stringent. This is shown in two-dimensional graph of figure 4.6 where x-axis shows vehicle age in 2001 and y-axis shows pollutants emitted in grams per VMT.[64] Even if we control for vehicle age, IM program emission point standards are less stringent than the standards for automobile manufacturers. This can be seen by the following example. Tier 0 standards imposed on automobile manufacturers since 1981 require vehicles to emit less than 0.41 g/mile of HC (as shown in column 1 of table 4.2). On the other hand, IM program cut-point for HC in IM program of Denver, Colorado, declares a vehicle normal emitter if it emits less than 5 gram/mile of HC, and high emitter if vehicle emits more than 5 gram/mile.

---

[64] Tier 2 standards, for example, beginning with vehicle model years 2004 (age = -3 in figure 4.6) are much more lower/stringent for CO than the Tier 1 standards required for vehicle model years 1991 to 2003 (age –2 to 10 in figure 4.6). Similarly, NOx and HC standards have also become more stringent for newer vehicles.

Even though IM program emission cut-points are much looser than the manufacturer standards, the complex problem of clearly defining a high-emitting vehicle remains unresolved due to the following questions. Should uniform cut-points for CO, NOx and HC emissions be established across all the technology groups of vehicles, so that more people would be encouraged to buy low-emitting cars rather than sport utility vehicles and trucks? Or, should the cut-points be made relative to the technological groups to encourage the introduction of low or zero-emission vehicle technologies? Further, the problem of choosing minimal cut-points is a very tricky and politically sensitive issue, because these choices can exempt a very small or very large fraction of vehicles from the regulatory purview of governmental intervention. If the cut-points are too high, very few vehicles are characterized as high-emitters. If they are relatively low, too many vehicles may be declared as high-emitters. The current fleet-average CO cut-point in Atlanta's IM program is 1.2% of CO_2 concentration, which means state regulators expect about 10% of the on-road vehicles to fail the initial IM test in one testing cycle. However, if the cut-point is chosen at 2.4%, then less than 5% vehicles will be expected to fail the test; while if the cut-point is chosen at 0.6%, then more than 20% vehicles will be expected to fail the test. The choice of emission cut-points to define a high-emitter is a meta-choice decision and needs careful normative evaluation. For the descriptive analysis in this research, I will treat IM emission cut-points as exogenously set IM program design parameters that are used to distinguish normal from high-emitters. Design parameters of Atlanta's regulatory IM program are shown in last row of table 4.1, which I discuss in greater detail in next section.

4.3 The IM program in the Atlanta airshed: the rules of the regulatory game in the southeastern USA

Atlanta's first IM program was established in 1981, covering the three ozone non-attainment area counties of Fulton, Cobb and DeKalb, and it was implemented in a decentralized test-and-repair network. Fast-growing Gwinnett County was added in 1986. Testing was originally required for the latest ten model year vehicles, but was expanded in 1986 to include the latest twelve model years. Inspections were conducted on an annual basis.

In response to the 1990 Clean Air Act Amendments (CAAA), the Georgia legislature revisited emissions testing in 1992.[65] This legislation enabled the Georgia Department of Natural Resources (Ga-DNR) to upgrade Georgia's IM program to an "enhanced" program, bringing it into compliance with the 1990 CAAA and new federal IM regulations. This enhanced version of the program received limited implementation in October 1996,[66] with emission inspections required only for those vehicles migrating to the Atlanta IM program area. The new program commenced in January 1997, with biennial emissions testing required of all vehicles from the 1975 model year to two years of age.[67] The new program also spanned the 13-county non-attainment area, incorporating nine new counties that were not subject to the previous basic IM program (as shown in figure 5.2). This study focuses on the first five years of the Atlanta "enhanced" IM program, during which time vehicles younger than 5 years of age were inspected using a two-speed idle (TSI) testing procedure (that measures emissions under idle and a 2500 RPM engine speed), while vehicles older than 5 years were inspected through ASM tests.[68]

As table 4.1 shows, Atlanta's IM program had a "hybrid" testing network. A 'fleet-average' vehicle failed the test if it emitted more than 220 ppm of HC and/or 1.2% of

---

[65] 1992 Georgia Air Quality Act, Article 2: Motor Vehicle Emissions Inspection and Maintenance Act (OCGA Section 12-9-40 et seq.).

[66] October 1996 was chosen as the soonest possible start-up date after the previous basic IM program, which operated during a January-to-April vehicle registration "season." Vehicle registration is now conducted year-round in Georgia, as is enhanced emissions testing.

[67] Three significant changes have recently been made to the Atlanta enhanced IM program. The waiver limit increased in January 2000 to $608, which represents $450 plus increments based on the consumer price index and fulfills EPA requirements. In 2001, testing frequency changed from biennial to annual; the requirement to inspect back to 1975 model years was replaced with the requirement to inspect the latest 25 model years; and the exemption of the two newest model years was changed to exempt the newest three model years.

[68] Changes have been made to the program since the first two-years of operation, which are the focus of this analysis. For example, the program began to require vehicles over six years of age to undergo the more rigorous Acceleration Simulation Mode (ASM) testing in October 1998. The primary difference between ASM and TSI testing is the approximation of real-world driving conditions, i.e., placing the engine under load. While the emissions inspector depresses the accelerator to achieve 25 miles per hour (MPH), ASM testing places the vehicle's drive wheels on a treadmill-like dynamometer that applies a 25 percent load on the vehicle engine. The latter approach is more representative of actual driving conditions than an idle test.

CO.[69] Visual checks of the catalyst and gas cap were also part of the vehicle inspection. The gas cap was also inspected to ensure that there were no excessive evaporative emissions. Between 1997 and 2000, IM program in Atlanta was "biennial"; however, in 2001, the IM program was changed from "biennial" to "annual" testing for all LDGVs and LDGTs. Furthermore, vehicles less than 2 years of age and older than 1975 model year were exempted from testing between 1997 and 2000; while in 2001, vehicles less than 3 years of age were exempted from testing. The quasi-experimental mixed-pooled research design (presented in chapter 5) enables quantification of the impact of changes in Atlanta's IM program rules between 1997 and 2001 on tail-pipe vehicular emissions from year to year.

4.4 Prior research on evaluating the vehicular tail-pipe emission reduction effects of IM programs by using remote sensing data

IM programs have been evaluated by using in-program IM data (Ando, McConnell et al. 1999; Environ 1998; Glover and Brzezinski 1997; Sierra-Research 1998; Wenzel 1999a), roadside emissions inspections data (CARB 2000), ambient air quality data (Scherrer and Kittelson 1994) and simulation computer models such as MOBILE and EMFAC. NRC (2001) and EPA (2002) explicitly suggest that each of these four data techniques have inherent biases and preferably should not be used independently for evaluation of IM programs. In-program IM data cannot estimate the fraudulent behavior by drivers or test centers (phenomena of clean-piping), neither can it correctly estimate the program avoidance rate (migration of vehicles outside the IM program boundaries). In addition, it has been suggested that the evaluations based on IM program data over-estimate the emission reduction benefits due to a statistical phenomena called as "regression towards the mean" (DeHart-Davis, Corley et al. 2002; Stedman, Bishop et al. 1997).

Roadside emissions inspection data has sample biases – called self-selection bias -- since it includes only those vehicles in the sample, which are volunteered by their drivers. One study found that self-selection bias leads to under estimation of the high-emitters by the roadside emissions inspection data (Stedman, Bishop et al. 1994). This study found that about 30% of the vehicles pulled over refused the voluntary test for one reason or another in a 5-day survey during July 15-19, 1991, in various northern

---

[69] Note that both idle and ASM tests use concentration ratios to measure CO and HC in Atlanta.

California locations. Remote sensing measurements revealed that the average on-road CO and HC emissions of those vehicles that refused inspection were more than double those of the vehicles that volunteered for inspection. This study thus concluded that the results from the roadside surveys may be biased low because the small fraction of high-emitting vehicles is under represented in the self-selected sample. Using biased information could significantly under-predict overall on-road fleet emissions or artificially over-predict IM effectiveness. Further, this data collection method has higher costs, as it has been reported that only about 25 vehicles per day can be tested with this methodology (Wenzel, Gumerman et al. 2000b).

Ambient air quality data cannot separate emissions of mobile sources, such as automobiles, from emissions of industrial or other sources. Finally, computer simulation models have major limitations; they estimate emission factors from small samples of laboratory derived emissions data, they have optimistic repair effectiveness assumptions, and they employ little model validation using real-world emissions data (Harrington, McConnell et al. 1998).

NRC (2001) cites several advantages of remotely sensed on-road vehicle emission data for evaluating the IM programs. First, on-road vehicle emissions data is a cost-effective source of evaluation data compared with the higher per-vehicle costs of advanced dynamometer testing on a small sample of vehicles, the original evaluation approach recommended by federal regulators. Second, on-road vehicle emissions data can also capture trends that cannot be discerned through internal inspection records alone, such as motorists avoiding the program and pre-inspection maintenance behavior. Third, on-road vehicle emissions data can also be used for a variety of purposes in addition to IM evaluation, including mobile source emission inventories, clean-screen programs that exempt low-emission vehicles from subsequent IM testing, and high-emitter programs that target polluting vehicles for off-cycle inspection and repair.

Despite the apparent weaknesses, the four data types -- in-program IM data, roadside emissions inspections data, ambient air quality data and computer simulation data -- can be used as baselines for comparison purposes with the results of on-road vehicle emissions data. This research uses primarily remotely sensed on-road vehicle emissions data to evaluate the impact on tail-pipe emission reduction effectiveness of the IM program due to the decision behaviors of drivers in the Atlanta airshed. The

remote sensing data collection methodology of on-road vehicular emissions is explained in further detail in section 4.4.1. Sections 4.4.2, 4.4.3 and 4.4.4 present three quasi-experimental methodologies – reference, step and comprehensive – that have been employed by previous researchers to measure the IM program emission reduction effectiveness by using remote sensing data.

4.4.1: Remote sensing of on-road vehicular tail-pipe emissions:

On-road vehicle emissions are measured through remote sensing by estimating the ratio of the pollutant (CO, HC, or NOx) to the amount of CO_2 in the exhaust plume. On-road vehicle emissions are thus a concentration ratio measurement rather than a mass emission rate measurement. Remotely sensed concentration ratios are measured in grams of pollutant per gram of fuel, while mass emission rates are measured in grams per mile for a specific driving cycle. The remote sensing measurement takes place in about one-half of a second. This is in stark contrast to dynamometer tests, which are mostly employed in IM tests during which emissions are measured over a variety of driving modes, such as IM240 takes 240 seconds.

Stedman (1989) first reported the use of remote sensing to measure pollutant concentration ratios from on-road vehicle exhaust plumes. Spectroscopic measurements detect the emissions in vehicle exhaust. Although absolute emissions concentrations in the exhaust plume change rapidly as the plume disperses, the ratio of the CO, HC and NO emissions to CO_2 stays the same over the time of measurement. A computer calculates the best slope of the ratio pollutant to CO_2 by using multiple spectroscopic readings taken in the approximately 1/2 second of total measurement time. Combustion equations translate emissions measurements into percent, or weight of emissions per weight of fuel used. Appendix A presents combustion equations that are used in previous studies as well as in this dissertation to convert pollutant concentration ratios into grams of pollutants per gallon of fuel used. The dependent variables in equations 1.7, 1.8 and 1.9 are measured in grams of pollutant per gallon. Further, two comparative methodologies—fuel-sales per year based and VMT per year based -- are also presented in appendix A. VMT data-based methodology is used in this dissertation to convert the grams of pollutants per gallon (mass emission factors) into tons of pollutants per year (mass emission rates).

The remote sensor uses a video frame of the measured vehicle's license plate, which is later matched with the vehicle registration data to get information about the rest

of the parameters associated with the measured vehicle, such as VIN, MY, and address of the owner. Further, the VIN can be decoded to get additional information about various technological parameters of the vehicle.

It can be inferred from observing the high on-road emissions under particular driving modes that emission control equipment on the vehicle has likely deteriorated or is broken. There are also driving modes under which a "clean" normal-emitting vehicle could produce high-emissions. These exceptional modes include: (1) cold start, when the engine and catalytic converter have not reached operating temperature, (2) at low load HC concentrations in the plume may be high, and (3) during the fuel enrichment, when the vehicle purposely operates with extra fuel, such as under high-load conditions. There are thus large uncertainties associated with separating high-emitters from normal-emitters through just the use of remote sensing data.

Due to these uncertainties, remote sensing has been under utilized in IM programs (NRC 2001). There are potentially three additional reasons for under utilization of remote sensing data. First, there is lack of standardization in remote sensing quality control and data reporting. A recent CRC project (Slott 2002), however, shows that a standardized remote sensing protocol is in the offing. Appendix B in Slott (2002) details how remote sensing sites should be described, what data should be obtained, and how data should be reported. The AQL has started to collect the remote sensing data under this protocol since 2000. Second, there is uncertainty associated with the quantitative significance of a measurement made over only about a half second during which there is no control over the driving mode of the vehicle. Third, there are issues about the accuracy of the emission measurements. Researchers have estimated the accuracy of the remote sensing measurements by comparing exhaust emissions measured on-board a vehicle to those measured external to the vehicle using remote sensing equipment. Lawson et al. (1990) and Ashbaug et al. (1992) showed that a remote sensor measures CO within ± 5% and HC within ± 15%. The NOx measurements have recently increased in accuracy within ± 5% error rate, as reported by Pokharel et al. (2001).

Using on-road vehicle emissions data, Wenzel et al. (2000a), EPA (2002) and DeHart-Davis et al. (2002) suggest that there are three quasi-experimental methods to determine on-road emission reduction effects caused by policy interventions such as Inspection and Maintenance (IM) Programs.

First, the "reference method" compares on-road vehicle emissions for the vehicles registered in the IM program area with those registered in a non-IM program reference area. The reference method, however, has a key limitation. The straightforward comparison of emissions data in one area with those in a reference area must be corrected for the physical and socio-economic differences between regions in which emissions might vary regardless of the presence of an IM program.

Second, the "step method" compares vehicular emissions tested under a newly instituted IM program with vehicular emissions in the same area that have yet to be tested under the new program. The limitation of this method is the inherent incompleteness of accounting for emission reductions. The emission reduction benefits might not account fully for non-compliance with the program or for preemptive repairs made in anticipation of the IM test.

Third, the "comprehensive method" tracks changes in emissions for vehicles that pass the test (the quasi-experimental control fleet), those that initially fail and then pass (the cooperative fleet), and those that fail and never pass, or avoid the IM program (the non-cooperative fleet). This method is limited because it requires enormous data sets for both IM and remote sensing on-road vehicle emissions to track the vehicle emissions before and after the IM tests. Further, the comprehensive method must account for seasonal variations to analyze the emission reduction effects.

In the past few years, many state-sponsored and independent research studies have employed these three empirical methods to evaluate the effectiveness of IM programs in the United States.[70] They provide mixed evidence for IM programs' success in reducing on-road vehicle emissions. Pierson (1996) effectively summarizes IM evaluation studies up to 1995; however, NRC (2001) reviews these evaluation studies more comprehensively. The following sections discuss the key results and methodological critiques of these studies, according to three empirical methodologies: reference, step and comprehensive. The results of important studies using each of these three methodologies are summarized in Table 4.3.

---

[70] Note that the effectiveness of IM programs in these three methods is calculated by comparing the emissions concentrations of an experimental fleet with a control fleet of vehicles. Effectiveness is thus measured as a unit-less percentage change in CO, HC and NOx emissions of experimental fleets as compared to control fleets.

Table 4.3: The IM effectiveness results of the prior studies according to three empirical methodologies: reference, step and comprehensive

Prior Studies	CO (% reduction)	NOx (% reduction)	HC (% reduction)
Reference Method			
Zhang et al. (1993)	13%	Not investigated	Not significant or 0%
(Rodgers, DeHart-Davis et al. under review)	15% cars and 10% trucks	Not investigated	Not investigated
(DeHart-Davis, Corley et al. 2002)	26% cars and 20% trucks	Not investigated	Not investigated
Step Method			
Stedman et al. 1997	5 to 9%	Not significant or 0%	Not significant or 0%
Corley et al. 2003	11.5% and 4.9%	Not investigated	20.1% and 3.1%
Comprehensive Method			
(Klausmeier and Weyn 1997)	9%	Not investigated	9%
Wenzel 1999b	7%	Not investigated	11%
Wenzel et al. 2000b	10%	5% increase	4%
Wenzel (2003)	3 to 4%	Not significant	Not significant

4.4.2 Reference method studies

The reference method involves comparing on-road vehicle emissions data from vehicles registered in an IM program area to vehicles registered in a non-IM program "reference" area[71]. The reference area, by virtue of its lacking an IM program, serves as a surrogate untested fleet, and thus can be used as a quasi-experimental control group. The difference in fleet emissions between the IM program area being evaluated and its reference area represents the emission reductions attributable to IM program effectiveness. In addition, these emission differences can also be compared with other reference areas or model predictions.

In a study to evaluate the Colorado IM program using the reference method, Zhang et al. (1993) found no significant Hydrocarbon (HC) emissions difference between cars from counties in Colorado with IM programs and cars from counties that did not have IM programs. They did find, however, that the IM group had 13% lower CO, and a lower percentage of CO gross emitters, than the non-IM group. They concluded that Colorado program was effectively reducing CO emissions, but it was ineffective in reducing HC emissions.

---

[71] The reference method may also be used to evaluate one IM fleet with another IM fleet.

The Air Quality Laboratory (AQL) of Georgia Institute of Technology applied the reference method to evaluate the effectiveness of the basic IM program in effect in Atlanta in 1994. The 4-county IM area was compared with the surrounding 9-county non-IM "reference" area of the broader Atlanta Metropolitan Statistical Area (MSA). The results of this evaluation indicated that the basic IM program in Atlanta was more effective for cars than predicted by the MOBILE model, but less effective than predicted for light duty trucks (Rodgers et al. under review). More specifically, the analysis indicated that car and truck emissions for carbon monoxide (CO) were 15 and 10 percent higher, respectively, in the uninspected nine county reference fleet than in the inspected four-county IM fleet.

IM program coverage in Atlanta was enhanced from a 4 county to a 13 county area in October 1996.[72] Later, the AQL also evaluated the enhanced IM program of Atlanta airshed using the reference method (DeHart-Davis, Corley et al. 2002). This study compared on-road vehicle emissions of the 13-county IM program area in the Atlanta MSA with two non-IM program "reference" cities of Augusta and Macon, and also compared emissions differences in IM and non-IM fleet vehicles with those predicted by a regulatory computer model. Assuming that on-road emissions differences represent observed effectiveness and model-predicted emissions differences represent effectiveness goals, this study found that the Atlanta enhanced IM program appears to be achieving 83 percent of its targeted emissions reductions. More specifically, the study estimated that the enhanced Atlanta IM program reduced CO emissions by 26 percent for cars and 20 percent for trucks on average for the first two years of the program. The authors accepted the confounding problems associated with the reliance of the reference method on finding a representative non-IM fleet, which may differ in characteristics for which controls are difficult to identify. Such potential characteristics include discrepancies in maintenance trends, socioeconomic conditions and vehicle quality.

The validity of the reference method therefore depends upon selecting a reference area without distinctive characteristics that could systematically bias the

---

[72] From 1986 to 1996, the Atlanta IM program boundaries covered four counties: Fulton, Dekalb, Cobb and Gwinnett. The following 9 counties were added under the enhanced IM program from January 1997 onwards: Cherokee, Clayton, Coweta, Douglas, Fayette, Forsyth, Henry, Paulding, and Rockdale.

evaluation. The IM program area and reference area should be similar in all the relevant parameters affecting vehicle emissions such as vehicle types, vehicle models, socio-economic characteristics of vehicle owners, altitude, climate, and fuel (EPA 2002). In 1997, nevertheless, EPA and Sierra Club researchers declared the reference method to be the preferred method for IM program evaluation, and they even suggested that all IM programs being evaluated should be compared with the reference Arizona IM program (EPA 1998; Sierra-Research 1997). This EPA preference for the reference method has been criticized by other researchers (Rothman 1998; Wenzel and Sawyer 1998a). Wenzel and Sawyer's (1998a) concerns included possible sample bias in recruitment options and the errors in the conversion of concentrations to mass emission rates. They also criticized the method of model-year stratification, in which vehicles are grouped by model year, and argued that this method does not accurately group vehicles according to the technologies used in a vehicle's fuel delivery and computer control systems. Rothman's (1998) concerns included recruitment bias and use of the MOBILE model to acquire evaporative emissions from a pressure test. The EPA retracted their preference in 2001, and now officially allows the states with IM programs to also use the step and comprehensive methods of evaluation, which are discussed below.

4.4.3 Step method studies

A second IM evaluation approach using remote sensing, known as the step method, compares inspected with uninspected vehicles during the first year of a new or upgraded program. The uninspected vehicles comprise an internal control group against which to compare the emission reductions of the inspected vehicles. Because this method applies to the early phases of a new or improved program, it can be used only once to assess program effectiveness.

A recent remote sensing study of the Colorado enhanced IM program compared odd (inspected) and even (uninspected) model year vehicles at the end of the first year of a new biennial enhanced IM program (Stedman, Bishop et al. 1997). At that point in program history, all odd model year vehicles should have been inspected, whereas all even model year vehicles were not inspected. This timing rendered even model year vehicles, the untested control group, to be compared with the odd model year vehicle emissions. The comparison of odd and even model year emissions suggested that Colorado's enhanced IM program had reduced CO between 5 and 9% percent, while HC and oxides of nitrogen (NOx) showed no improvement.

More recently, the AQL also used the step method to estimate the benefit of an enhanced IM program in the 13-county area of the Atlanta region. This study compared emissions of vehicles that had been tested with those that had not been tested when the IM program expanded in October 1996 to include the surrounding nine counties. This study found that the IM program has resulted in an 11.5% reduction in CO and a 20.1% reduction in HC emissions (Corley, DeHart-Davis et al. 2003).

Three factors limit the validity and generalizability of the step method study results to evaluate IM program effectiveness. Measurement of on-road vehicle emissions takes place in fewer locations, which avoids any confounding socioeconomic or physical influences at different sites, but limits generalizability to the overall fleet. A second limitation is that these studies measured vehicles transitioning from an annual basic IM program to an enhanced IM program, rendering it an evaluation of incremental program effectiveness and not a complete estimate of IM program performance. NRC (2001) describes this method as suffering from a "limitation of inherent accounting incompleteness" since emission reduction benefits do not account fully for non-compliance with the program or for preemptive repairs made in anticipation of the IM test. The third limitation is that the control group of untested vehicles may not be the correct control, because confounding demographic and technological factors may not be actually randomly distributed between tested and untested fleets of vehicles as required by the design assumptions of the step method.

4.4.4 Comprehensive method studies

The comprehensive method averages the emissions of vehicles measured before initial and after final IM testing, with the difference attributed to IM program effectiveness. Emissions differences can also be generated for various sub-fleets, such as vehicles initially failing and ultimately passing the IM test versus failing vehicles that never receive a final pass. This approach enables a variety of IM-related analyses, such as deterioration rates of IM repairs, the influence of pre-IM repairs on emissions baselines, and a comparison with estimates based on IM records alone. The major disadvantage of this approach is the enormous volume of on-road data required to measure a representative sample of vehicles before and after IM testing. Sample size requirements hinge on the probability of measuring on-road vehicles within a specific time period of IM testing, a probability that fluctuates with testing frequency and the distribution of sampling throughout the year.

The earliest evaluation that used the comprehensive method to evaluate California IM program is found in Lawson et al. (1990), which compared remotely sensed 1989 data with the California IM program data and found that (1) there were a number of high-emitters that had passed their last biennial test, even within the past 90 days, and (2) the size of the disparity was almost independent of the length of time elapsed since the last biennial test. These results implied that either the biennial IM test was improperly conducted or that the high-emitters became high-emitters very soon after their biennial IM test.

Another remote sensing study in California in 1996 compared the on-road emissions of 3.5 million vehicles 30 to 90 days before with up to 90 days after their basic IM test (Klausmeier and Weyn 1997). For those vehicles that failed their initial smog check and then passed, both CO and HC emission differences registered at 20 percent. Normalizing this result to the entire fleet yielded an estimated nine percent emissions reduction in HC and CO. A third evaluation, of the Arizona enhanced IM program in 1997, analyzed four million remote sensing measurements on 1.2 million vehicles in the Phoenix IM area (Wenzel 1999b). The results indicated a seven percent reduction in CO and an 11 percent reduction in HC.

A fourth study used the comprehensive method to estimate the effectiveness of the California South Coast Air Basin's enhanced IM program in 1999 (Wenzel, Gumerman et al. 2000b). "Smog Check" IM records were used to delineate tested from untested vehicles by the existence of an enhanced inspection within the past twelve months. A comparison of these vehicle groups indicates a ten percent reduction in CO, a four percent reduction in HC, and a five percent increase in NOx. In another study focused on IM program in Phoenix, AZ, Wenzel (2003) reported 3 to 4% decrease in CO, while NOx and HC were found to be not significantly reduced for experimental groups before and after IM tests.[73]

There are potentially three key limitations of the comprehensive method. The first limitation is the increased cost of the evaluation study because huge volumes of on-road vehicles emissions data and IM program data must be collected and analyzed. A second

---

[73] A more disturbing finding of Wenzel (2003) concerned the fact that the use of comprehensive, step and reference methods in the same study area – Phoenix AZ – provided results that were not the same. Wenzel (2003) argues that the results from three methods are not comparable; but then the question arises which method should be treated as more representative of estimating the emission reduction effectiveness due to IM programs.

limitation in the comprehensive method is the potential seasonal effects[74] that result from the year-round testing required to obtain adequately sized samples. A third limitation is that users of this method have also tended to rely on a few high-volume sites, yielding a large number of repeat vehicles that lower the fraction of unique vehicles that could be reached at a greater number of sites.

Despite these limitations, the comprehensive method has four key advantages over the reference and step methods of evaluation (EPA 2002: 47-48): (1) The initial emissions reductions attributable to the program can be independently measured, and can be compared with those measured by the program itself. (2) The repair effectiveness over a short-term (i.e. up to 2 years after final IM testing) can be independently measured. Short-term repair effectiveness can be compared with long-term repair effectiveness as measured using multiple years of in-program data on the same vehicles. (3) The effect of pre-test repairs on average emissions can be measured. (4) Because large numbers of remote sensing measurements are made, the comprehensive method allows the identification of vehicles that do not report for, or do not complete, IM testing, yet are still being driven in the IM area.

As the literature review for all the three methods of evaluation indicates, the IM program effectiveness in the Atlanta airshed has so far not been evaluated by using a comprehensive method of evaluation. The two reference method studies of Atlanta covered periods 1994-5 (Rodgers et al, under review) and 1997-8 (DeHart-Davis et al, 2002), while the step method study covered the period 1996-7 (Corley et al 2003). There is wide discrepancy between the results of these three studies that measure IM program emission reduction effectiveness in the Atlanta airshed: CO appears to be reduced anywhere between 11.5% to 26% for cars (and 4.9% to 20% for trucks). Only Corley et al. (2003) measured HC reduction at 20%, while no study has so far investigated the impact of IM program on NOx emissions.[75] This study estimates IM program effectiveness for CO and HC emission reductions for each year between 1997 and 2001; and for NO emission reduction between 1999 and 2001. The methodology is described in chapter 5 and the results are presented in chapter 6. While the measurement of IM

---

[74] The seasonal effects include variation in temperature, pressure, humidity, fuel mixes, which are not always precisely measured during remote sensing data collection.

[75] It was not an explicit objective of Atlanta's IM program to reduce NOx emissions during the three study periods (that range between 1994 to 1998). NOx controls were added to Atlanta's IM program in 1999 (SIP 1999).

program emission reduction effectiveness is an important issue, it is equally important to study the underlying effects of drivers' decision behaviors on vehicular emissions, which is also attempted in this study. Next, studies that investigated decision behaviors of drivers in response to IM programs are briefly reviewed.

4.5 IM programs and vehicle owners' decision behavioral research studies

The motorist compliance rate has been the predominant decision behavioral aspect of IM program intervention that has been studied in some detail by recent researchers (Harrington, McConnell et al. 1999; 2000; 1998; Lawson 1993; 1995; Lawson, Groblicki et al. 1990; Wenzel 1999b; Wenzel, Gumerman et al. 2000b).[76] The compliance rate refers to the percentage or fraction of vehicles that are required to participate in an IM program that actually do so (NRC 2001: 190). Harrington et al. (1998: 27-8) postulated that there could be four kinds of non-compliant vehicles: (1) those that are not registered, (2) those that avoid the program by registering outside the area, (3) those that are registered but never take the test, and (4) those that take the test and fail but never complete the test cycle with a passing test. All of these four kinds of non-compliant/non-cooperative behaviors with respect to IM program have been extensively discussed in previous research (all but the first kind are empirically estimated in this dissertation for the case study of Atlanta airshed).

The first kind of non-compliant drivers avoid the IM program by not registering their vehicle at all. Since they do not have any record in the vehicle registration data, it is very difficult to track them; and as far as I know, no empirical study has estimated percentage of non-registered vehicles in an IM program area. Data available with the traffic police authorities might shed some light on the extent of vehicles that are in operation without valid registrations.

The second kind of non-compliant behavior of motorists concerns those who register their vehicles outside the IM area but continue to drive in the area in states having an IM program determined by county-line boundaries. Stedman et al. (1997), for example, reported the migration of registration of high-emitters outside of Denver's centralized IM 240 program area, but they continue to be driven in the area. McClintock

---

[76] In addition to motorist compliance, behavioral studies related to IM program have also focused on behavior of IM testing station personnel, automobile manufacturers, dealers and retailers, and in a broad sense, the over-all driving behavior of motorists. I focus on motorist compliance in this dissertation.

(1999) reported similar migration of high-emitters in Ohio at the start of their IM 240 program.

The third kind of non-compliant behavior concerns those vehicle owners who register their vehicles without duly passing an IM test. This is done either by fraudulent repairs (i.e. tampering[77] with vehicle emission control systems), bribing IM test stations[78] or bribing vehicle registration authorities. The California Air Resources Board report (CARB 1985) used random roadside pullover inspection data from vehicles in California in 1985 and concluded that the IM smog check stations were adequately performing the emissions test but were failing to identify most of the tampering, and that, in the Los Angeles basin, tampering before and after the smog check were prevalent.

In another study using annual random roadside surveys of about 11,000 vehicles in California, Lawson (1993) found no difference in emission rates in vehicles inspected and not inspected under the California IM program. Over-all failure rates were about 40%, which is about twice the failures rates normally recorded in the biennial IM tests. The emission rates and failure rates of the cars were again independent of where they were in the biennial cycle. Nearly half of the high emitters seen in the roadside tests went on to pass their subsequent biennial IM test on the first try. Based on this evidence, the author suggested that vehicles are being falsely passed and their emissions are unaffected by the California IM program.

Additionally, using the same survey data, Cadle et al. (1994) and Lawson (1995) showed failure rates no lower, or at best only marginally lower, for IM inspected vehicles than for non-IM inspected vehicles. Further examination of the survey data showed the lowest tampering rates and lowest emissions failure rates in test-only IM locations, and highest failure rates in test-and-repair IM locations. These studies apparently confirmed EPA's hypothesis that tampering rates were higher in decentralized testing networks than centralized networks. NRC (2001: 59 footnote 2), however, suggests that no comprehensive study has yet been done to support or reject EPA's hypothesis. The

---

[77] Tampering is defined as the malfunctioning of one or more emissions-control devices due to either deliberate disablement or mechanical failure (NRC 2001: 224).

[78] IM test-and-repair stations in decentralized testing networks have the incentive to pass the otherwise failing vehicles to maintain a good rapprochement with their (regular) customers and increase the long-term demand for their inspections. On the other hand, test-and-repair IM stations also have the opposite incentive to fail more vehicles because it can increase their short-term demand for emissions-related repairs. For detailed discussion of incentives for decentralized IM testing networks, please see Hubbard (1998).

NRC (2001:59) report asserts "testing fraud has been reported in both centralized and decentralized testing networks. Since there are many more stations performing inspections in the decentralized network, the number of stations cited for testing fraud will likely be higher compared to a centralized program. However, the number of inspections an individual station may be performing could be low whereas testing fraud at a high-volume centralized testing facility may impact a large number of tests. The committee could not find a rigorous comparison of these program types to state definitively that the number of vehicles impacted by testing fraud is greater in a decentralized program." So there is no conclusive evidence whether centralized or decentralized testing network better avoids false passes of high-emitting vehicles, but the evidence is clear that testing fraud occurs in both kinds of networks.

The fourth kind of non-compliant behavior concerns those high-emitters who fail the initial IM test but never appear for re-inspection (also called "unresolved failures), which has been reported by Wenzel (1999a), Wenzel et al. (2000b) and Ando et al. (2000). In Colorado, for example, the percentage of unresolved failures in the enhanced IM program increased from 23% to 27% between 1998 and 1999. Remote sensing data in IM program areas has consistently shown these unresolved failures still operating inside IM program areas.

NRC (2001: 190) explicitly accepts that "the negative effect caused by this poor compliance element has not been well documented." NRC (2001: 193) therefore recommends that all kinds of non-compliant behaviors need to be estimated in any realistic evaluation of IM program. In this dissertation, I have listed 30 various non-compliant alternative paths available to high-emitters, which are shown in figure 1.3 and explained in section 1.3. Note that the four kinds of non-compliant behaviors discussed in the previous literature are included in the analysis of this dissertation; and in particular, an attempt is made to quantify the effect of drivers' decision behaviors on vehicular tail-pipe emissions (while controlling for other factors that affect emissions), which has not been as exhaustively reported in previous research. Another important issue mostly neglected in previous research concerns the fact that the outcomes of IM program intervention have not been evaluated on the basis of multiple values/criteria, such as fairness, which is explained in next section.

4.6 Multiple decision criteria evaluation of IM programs: Operationalizing a meta-decision model in the context of the Atlanta airshed

Notwithstanding the uncertainty about the decision behaviors of high-emitting vehicle owners, it is clear that these high emitters continue to contribute inordinately to the air quality problem and that improvement in this area would be cost-effective because small total expenditures on less than 10% of the fleet would result in considerable improvement in air quality for all the affected residents of the Atlanta airshed. From these studies, one can infer that if the potential for cost-effective vehicular emission reductions, designed on the assumption of a Polluter Pays Principle (PPP), were the only value at issue, the IM program would potentially be an effective regulatory strategy for improving air quality. It could be argued, however, that the PPP is not applicable in this situation since it can be hypothesized that high emitting vehicle owners cannot sustain further repair costs, because they have little disposable income. The enactment of a regulatory program, such as an IM Program, is not in itself enough to induce the high-emitting vehicle owners to bear the repair costs, nor does the threat of punishment elicit cooperation and timely repairs by high emitters.

The National Research Council (NRC 2001:5) recommends: "Further research is needed to design the means to reduce high emitting vehicles in ways that are effective *as well as socially and politically acceptable* [my italics]. States would have to evaluate which policies are the most cost-effective and acceptable ways of obtaining emissions reductions from high-emitting vehicles." The NRC recommendation implies that there are multiple evaluative criteria for judging policies to improve air quality. While the cost-effectiveness criterion may be the most important in some situations, the application of a fairness criterion may suggest rule changes that would increase drivers' cooperation with the emissions laws. The NRC recommendation apparently leads one to apply multiple criteria decision-making models (MCDMs) for evaluating the IM programs, which has so far not been attempted in previous research. While a full multiple-criteria study is beyond the empirical scope of this dissertation, I use two values – emission reduction effectiveness and fairness – to evaluate the impact of IM program in the Atlanta airshed between 1997 and 2001.

More specifically, as explained in section 3.4 on the generalized methodology of MDMs, I use the case-study of IM program intervention in the Atlanta airshed to describe the context-sensitive outcomes on two value scales: (1) I describe the effect on vehicular

tail-pipe emissions due to the decision behaviors of high-emitting vehicle owners under the given regulatory incentive mechanism; and (2) describe the impacts/outcomes measured on the value of the fairness due to the IM program intervention. Fairness is defined as the null hypothesis that median household income of the vehicle owners' residential census block groups is statistically equal for all IM eligible fleets, including control, cooperative and non-cooperative fleets.[79] Both of these questions/criteria/values are explored in greater depth with empirical data in chapters 5 and 6. Once the results from the descriptive analysis –i.e. level of action – are presented in chapter 6, I also briefly talk about normative analysis part of MDMs in chapter 7; that is, how the incentive mechanism design of IM program in Atlanta airshed could be changed to make it more effective in reducing vehicular tail-pipe emissions (by increasing the cooperation of high-emitting vehicle owners) and fairer in distributing the program costs as compared to the results seen for the periods 1997 to 2001.

---

[79] This null hypothesis is a statistical representation of the GINI-coefficient decision rule that has been used extensively in policy analysis to measure the fairness effects of the public policy interventions.

CHAPTER 5

THE QUASI-EXPERIMENTAL RESEARCH DESIGN

5.1 The rationale for a quasi-experimental design

While controlled laboratory experiments provide experimenters the opportunity to explicitly control the timing and the sample of intervention, natural experiments – also called quasi-experiments – study the effects of an intervention that has been introduced at a time for a population that is not in the control of the experimenter. Both controlled experiments and quasi-experiments, however, share the methodological objective of estimating the intervention effects on the "treatment" groups as compared to the "control" groups of populations of interest (Cook and Campbel 1980).

Quasi-experimental studies are commonly employed in policy analysis to estimate the effects of policy interventions on the objective variables (or outcomes) for which the policies were introduced.[80] The policy evaluation and implementation literature is also replete with quasi-experimental studies. Meyer (1995) provides a broad review of the previous quasi-experimental studies. This study employs quasi-experimental design because it provides a cohesive methodology to investigate in detail answers to the three major research questions that were introduced in chapter 1 (specifically sections 1.1 and 1.4). Quasi-experimental research designs not only provide a sound scientific methodology to objectively estimate the effects of the policy interventions, but the results also provide evidence for designing future policies, replicating the existing policy in other areas, or modifying the existing policy interventions to enhance the effectiveness of policies in meeting the multiple objectives/outcomes desired by policy-makers in particular, and society in general.   At the same time, quasi-experimenters walk a very tight rope because they do not enjoy the flexibility of controlling the timing and

---

[80] It is also possible to estimate through quasi-experimental designs the policy intervention effects in a pilot study area for a policy, which may or may not be actually implemented on large populations "after" the quasi-experimental study. Pilot policy interventions allow quasi-experimenters to control the timing and sample of experimental intervention, but the intervention effects are also measured "ex-post facto".

population/sample of interventions as do controlled lab experimenters. The control and treatment groups of sampled subjects may thus not be as clearly demarcated in the case of quasi-experiments as they are for controlled experiments. There are many other pitfalls and threats to the validity of the quasi-experimental research designs, which are extensively covered in previous literature (Cook and Campbell 1980, Rossi and Freeman 1993, Dunn 1998) and discussed later in this chapter in the context of the present study.

A brief introduction to the quasi-experimental research design of this study was presented in section 1.4. Chapter 5 builds on section 1.4 and presents the research design in full detail. In section 5.2, the broader concept of quasi-experimental research design employed in this study is elaborated to operationalize the methodology to test the hypotheses [introduced in section 1.3]. Section 5.3 introduces the remote sensing sample of on-road vehicles that was collected by the remote sensing team of the Air Quality Labs in the Atlanta MSA between 1997 and 2001. In section 5.4, the process of constructing a mixed-pooled time-series database is described and the sample statistics of the variables used in this study are presented. The database is constructed, first, by matching the remote sensing sample of the on-road vehicles with the vehicle registration data to get information about the vehicular parameters and the vehicle owners. Second, the remote sensing sample is also matched with the IM program data to track the emissions' testing records of the sampled vehicles. Third, climate data is used to ascertain the ambient atmospheric conditions on the days of the remote sensing measurements. Fourth, census data is employed to geo-code the addresses of the sampled vehicle owners at the census block-group level for getting information about socio-economic contextual parameters of the vehicle owners.

Section 5.5 presents the data analysis methodology, which is further subdivided in three subsections. Section 5.5.1 presents the methods to estimate the probability of cooperative and non-cooperative decision behaviors of high-emitting vehicle owners in the Atlanta airshed, extending the results from the observed sample to the Atlanta MSA. Section 5.5.2 presents the mixed pooled time series generalized linear regression models to evaluate the impact on vehicular tail-pipe emissions due to the vehicle owners' decision behaviors, while controlling for other significant parameters. Section 5.5.3 presents multinomial logistic regression models that are employed to explain the systematic variation in socio-economic and technological contextual conditions that affect the probability of cooperative and non-cooperative decision behaviors of high-

Environmental policy intervention to regulate the tail-pipe emissions from high-emitting vehicles, includes "enhanced" IM program that began in January 1997 in Atlanta

Quasi-experimental control and treatment groups of vehicle owners
- Control group [Normal emitting vehicle-owners inside IM program area]
- Treatment groups [(1) Cooperative high-emitting vehicle owners, (2) Non-cooperative high-emitting vehicle owners
- Other groups [Outside Atlanta fleet]

Technologies for tail-pipe emission control systems [AIR, OXY, TWC, EGR, CLL, TAC, PCV]

Context specific parameters
- Vehicular characteristics [vehicle age, vehicle type, mileage, fuel regime, vehicle manufacturer, country of vehicle manufacturer]
- Physical and natural parameters [ambient temperature, atmospheric pressure, relative humidity, road grade and time of measurement]

Socio-economic and demographic contextual conditions of vehicle owners measured at census block group level [per capita income, median household income, population age and gender composition, % of white, black and other races]

Environmental outcomes [Tail-pipe vehicular emissions of CO, HCs and NOx]

Figure 5.1: A conceptual schema of quasi-experimental research design

emitting vehicle owners. Finally, section 5.6 explores threats to internal, statistical, construct and external validity of the quasi-experimental research design.

5.2 The conceptual framework

Figure 5.1 synthesizes the conceptual framework of the quasi-experimental research design, various aspects of which have been discussed in detail in chapters 1 to 4. The "enhanced" IM program is the environmental policy intervention in the Atlanta airshed, which leads to two broad groups of vehicle owners: the control and treatment groups. The control group of vehicle owners include "initial test initial pass" vehicles $[Q_1]$.[81] Other control groups are the IM-ineligible fleet $[Q_2]$, waived fleet $[Q_3]$, rest-of-GA fleet $[Q_4]$ and the missing fleet $[Q_5]$. The treatment groups of vehicle owners include cooperative and non-cooperative fleets. Cooperative fleets include retest-pass $[Q_6]$ and migrated pass $[Q_7]$ vehicle owners. Non-cooperative fleets include retest-fail $[Q_8]$, migrated fail $[Q_9]$, missing fail $[Q_{10}]$ and missing passed $[Q_{11}]$.

Tail-pipe vehicular emissions are complex functions of human decision behaviors that emerge after the IM policy intervention is introduced [represented by 11 Q variables]. In addition, vehicular characteristics [represented by 31 R variables] and physical and temporal parameters at the time of measurement [represented by 7 S and 4 T variables] are also hypothesized to affect the production of tail-pipe vehicular emissions.

Human decision behaviors are also hypothesized to be affected by both group-level socio-economic and demographic contextual conditions [represented by 17 W variables] as well as individual level parameters captured by vehicular characteristics [represented by 31 R variables] and temporal parameters [4 T variables].

5.3 Remote sensing sampling of on-road vehicles in Atlanta (1997-2001)

Remote sensing data captures CO, HC and NOx tail-pipe emissions from on-road vehicle fleets, which are measured in percentage concentrations of CO_2. Section 4.4.1 in chapter 4 presents the general methodology of remote sensing of vehicular exhaust emissions. Appendix A presents atmospheric chemistry and transportation

---

[81] Since the initial test initial pass group of vehicle owners $[Q_1]$ may also include cooperative and non-cooperative vehicle owners, as described in the limitations of this study later in chapter 5, the $[Q_1]$ group may contain vehicles from the treatment groups. Further, in a narrow sense, vehicles in $[Q_1]$ also go through IM testing, so it can be argued that $[Q_1]$ should also be categorized as a treatment group. The use of the phrase "control group" for $[Q_1]$ should be interpreted in light of these limitations. The limitations show that the research pursued in this study has a "quasi-experimental" and not an "experimental" design.

research methods used to convert the emission concentration ratios into mass emission factors (grams of pollutant per gallon) and mass emission rates (tons of pollutant per year).

The raw remote sensing data between 1997 and 2001, collected by AQL, contains a total of 1.42 million observations measured at various locations in the Atlanta MSA. The license plates of the observed vehicles were matched by AQL researchers with the vehicle registration databases to get information about vehicular characteristics, such as VIN, make, model, model year. Further, the AQL team used a VIN decoder to get information about the technological parameters of the vehicles.

In the initial data-cleaning process of the raw data, I dropped the observations from the annual samples for which either the license plates were not clearly readable from the pictures of the license-plates taken by the remote sensors, or the license plates did not match with Georgia's vehicle registration databases. First, 285,040 observations with the un-readable license plates were dropped because no further information either about the vehicular characteristics or the vehicle owner can be ascertained. Second, 240,887 observations for license plates that were not found to be registered anywhere in the 159 counties of the state of the Georgia during that calendar year were dropped because access to vehicle registration databases of Georgia's neighboring states or the entire USA was not available.

The first reason –un-readable license plates-- to drop the observations may affect the randomness of the selected sample[82] because it is likely that very large trucks, vehicles with accidents and very new vehicles may not have the license plates at their normal rear-end positions where cameras of remote sensors are programmed to take pictures. Similarly the second reason – non-availability of vehicle registration data outside the Georgia state – probably limits the results[83] of this study in three ways: (1) High-emitting vehicle owners who avoid the vehicle registration altogether and drive illegally inside the IM program area (as shown in figure 1.3) are not observable because their "fake" license plates do not match with Georgia's vehicle registration database. (2)

---

[82] A t-test shows that 285,040 observations on the vehicles in the sample with no readable license plates have 0.0875% higher CO and 3.45 PPM higher HC concentrations than 1,138,284 observations on vehicles in the sample with readable license plates.

[83] A t-test shows that 240,887 observations on the vehicles in the sample with license plates not matched in the Georgia vehicle registration database have 0.0267% higher CO and 23.42 PPM higher HC concentrations than 897,397 observations on vehicles in the sample with readable license plates.

High-emitting vehicle owners who register out of Georgia and still drive inside the Atlanta's IM program area remain unobservable because information about the vehicles, such as VIN, which is crucial to the research design, is not available. (3) A fraction of the on-road fleet always comes from vehicles that are traveling through Atlanta area but are not registered in the state of Georgia. This is called as "out-of-state" fleet. Out-of-state vehicles are dropped from the sample because, first, no further information is available about them; and, second, out-of-state vehicles may or may not be subjected to the IM program regulations, which depends on the area of their registration. It should, however, be noted that any realistic tail-pipe vehicular emissions inventory should take into account the "out of state" vehicles, but emissions inventory building is not the focus of the present research.

The remaining "Georgia registered" samples observed for each of the five calendar years between 1997 and 2001 were sorted by VIN, observation date and time and then a new variable [unique: VIN = lag (VIN)] was computed to check whether a (unique-by-VIN) vehicle has been observed multiple times during a calendar year. If a vehicle was observed multiple times during a year, its last observation in the sample was retained.[84] This way, the sample is reduced to observations on "unique" vehicles during a calendar year, which facilitates its tracking in IM program data.[85]

Once annual samples of the raw data are cleaned as described in the previous two paragraphs, the remaining samples from each year are pooled together, which, in rest of the dissertation, is called as "mixed-pool time-series" sample data. The sample data has a total of 777,408 observations, of which 668,559 (85.9% of total sample) are unique (by VIN) vehicles. Of the total sample, 109,249 (14.1%) vehicles in the sample are observed at least twice, 17,320 (2.2%) are observed at least three times and 2,631 (0.3%) are observed at least four times in different calendar years between 1997 and 2001. The probability of observing the same vehicle again through a remote sensor drops exponentially in this sample.

---

[84] The last observation is retained to get the latest information within a calendar year about the vehicle's emissions. A t-test shows that 89,021 observations on the vehicles observed twice or more in an evaluation year in the sample have 0.0134% higher CO and 8.21 PPM higher HC concentrations than 777,408 observations on the vehicles uniquely observed in a given year in the sample.

[85] Note that this does not preclude multiple observations of the same vehicle from being retained in the sample if and only if it is observed in more than one calendar year.
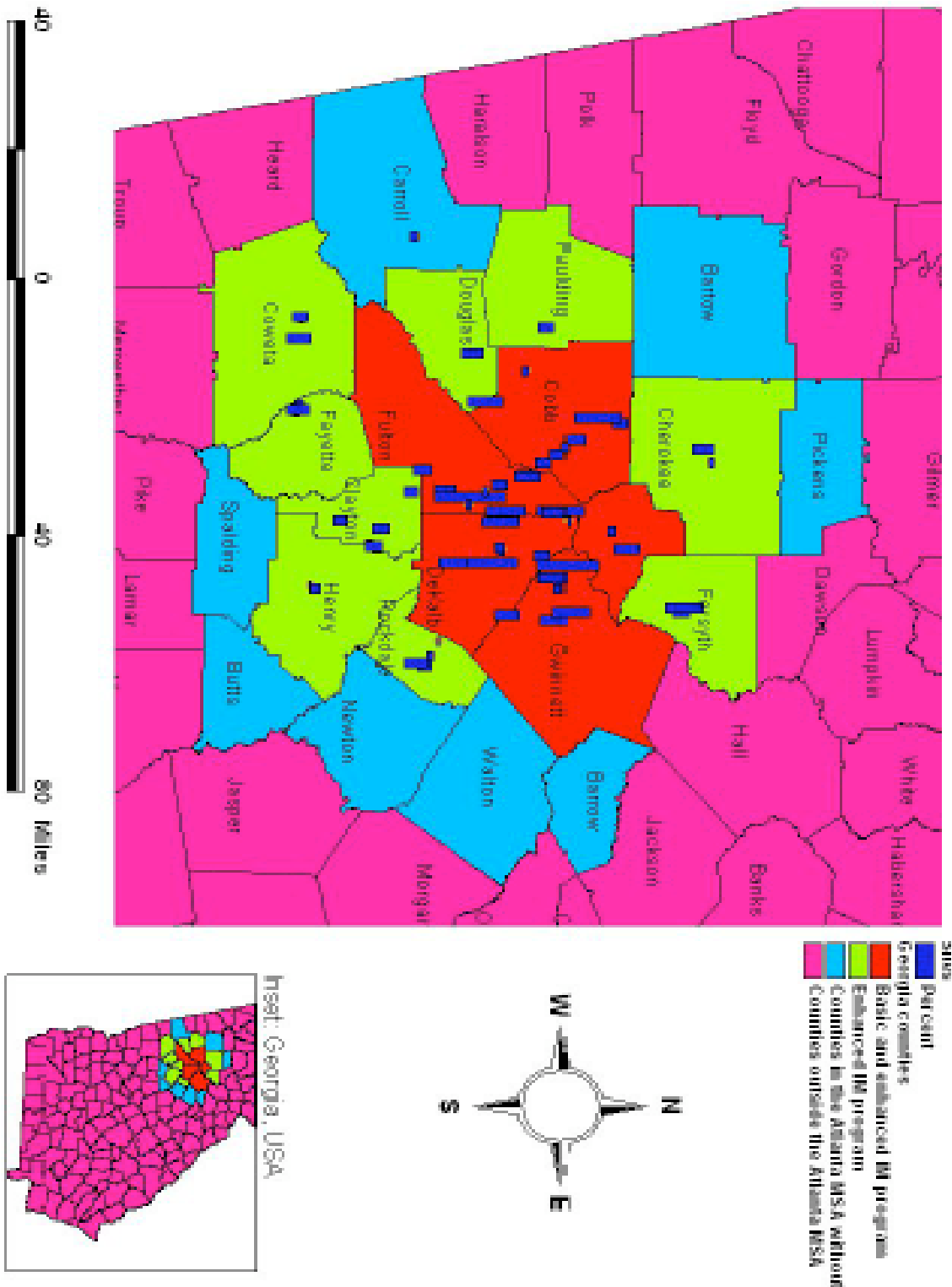
Figure 5.2: Observations as a percent of total sample at remote sensing sites in Atlanta (1997-2001)

Table 5.1: Descriptive statistics of the sample data (1997-2001)

Variable	Symbol	N	Minimum	Maximum	Mean	Standard Deviation	Skewness
Vehicular tail-pipe emissions							
CO (%)	CR_{CO}	775606	-1.52	14.75	.4796	1.07563	4.460
HC (PPM)	CR_{HC}	741869	-5000.00	55900.00	180.0408	1062.96255	13.082
NO (PPM)	CR_{NO}	136486	-249.00	6961.00	522.0066	761.36372	2.429
CO (gm/gal)	Y_{CO}	466640	2.88	4013.13	213.0044	396.0363	3.577
HC (gm/gal)	Y_{HC}	466640	.05	1524.35	18.65089	52.19493	9.457
NO (gm/gal)	Y_{NO}	89408	.04	269.19	24.73932	31.14795	2.225
Quasi-experimental fleet types representing vehicle owners' decision paths							
Control fleet	Q_1	777408	.00	1.00	.2701	.44402	1.035
In-eligible fleet	Q_2	777408	.00	1.00	.5213	.49955	-.085
Waived fleet	Q_3	777408	.00	1.00	.0023	.04761	20.910
Rest-of-Georgia	Q_4	777408	.00	1.00	.1018	.30234	2.634
Missing fleet	Q_5	777408	.00	1.00	.0378	.19064	4.849
Retest pass	Q_6	777408	.00	1.00	.0189	.13613	7.069
Migrated pass	Q_7	777408	.00	1.00	.0086	.09249	10.626
Retest fail	Q_8	777408	.00	1.00	.0037	.06106	16.256
Migrated fail	Q_9	777408	.00	1.00	.0011	.03347	29.808
Missing fail	Q_{10}	777408	.00	1.00	.0033	.05778	17.192
Missing pass	Q_{11}	777408	.00	1.00	.0314	.17452	5.370
Vehicular characteristics							
Vehicle age (years)	R_1	777408	-2	40	5.40	4.620	1.356
Vehicle type	R_2	733080	0	1	.38	.485	.508
FORD	R_3	777408	.00	1.00	.1694	.37512	1.763
GM	R_4	777408	.00	1.00	.1974	.39807	1.520
CHRYSLER	R_5	777408	.00	1.00	.0878	.28305	2.912
HONDA	R_6	777408	.00	1.00	.0785	.26889	3.136
TOYOTA	R_7	777408	.00	1.00	.0727	.25962	3.292
NISSAN	R_8	777408	.00	1.00	.0554	.22878	3.887
MAZDA	R_9	777408	.00	1.00	.0257	.15831	5.992
MITSUBISHI	R_{10}	777408	.00	1.00	.0124	.11059	8.818
MERCEDES	R_{11}	777408	.00	1.00	.0110	.10418	9.388
VOLVO	R_{12}	777408	.00	1.00	.0100	.09948	9.851
VW	R_{13}	777408	.00	1.00	.0076	.08668	11.362
ISUZU	R_{14}	777408	.00	1.00	.0082	.09016	10.910
Other Manufacturers	R_{15}	777408	.00	1.00	.2639	.44075	1.071
USA	R_{16}	777408	.00	1.00	.6069	.48844	-.438
JAPAN	R_{17}	777408	.00	1.00	.1594	.36609	1.860
CANADA	R_{18}	777408	.00	1.00	.0952	.29353	2.758
GERMANY	R_{19}	777408	.00	1.00	.0298	.17013	5.527
MEXICO	R_{20}	777408	.00	1.00	.0234	.15114	6.307
SWEDEN	R_{21}	777408	.00	1.00	.0150	.12147	7.986
KOREA	R_{22}	777408	.00	1.00	.0089	.09393	10.456
UK	R_{23}	777408	.00	1.00	.0034	.05842	17.001
Other countries	R_{24}	777408	.00	1.00	.0579	.23355	3.786
AIR	R_{25}	716710	0	1	.25	.432	1.161
TWC	R_{26}	716715	0	1	.96	.185	-5.011

Table 5.1 (Continued)

EGR	R_{27}	714765	0	1	.82	.385	-1.659
CLL	R_{28}	716714	0	1	.97	.178	-5.266
TAC	R_{29}	716714	0	1	.14	.345	2.103
OXY	R_{30}	716711	0	1	.03	.162	5.845
PCV	R_{31}	716715	0	1	1.00	.052	-19.020
Physical conditions at the time of remote sensing measurement							
Ambient temperature (F)	S_1	777408	17.00	97.00	67.9168	13.83790	-.536
Relative humidity (%)	S_2	777408	14.00	100.00	59.3126	17.94219	.268
Atmospheric pressure (Hg)	S_3	777408	28.49	30.22	29.0190	.16671	1.324
Speed (MPH)	S_4	777408	.30	74.60	37.7163	8.69647	.151
Acceleration (MPH/sec)	S_5	777408	-13.30	13.30	.7076	.57110	.198
Road gradient (degrees)	S_6	775273	-6.00	7.50	.7752	3.17212	-.125
Sine (road gradient)	S_6	775273	-.997495	.997495	.2282989	.6679658	-.494
Generation of instrument	S_7	777408	0	1	.22	.414	1.350
Temporal parameters							
1997	T_1	777408	.00	1.00	.2507	.43341	1.150
1998	T_2	777408	.00	1.00	.1836	.38718	1.634
1999	T_3	777408	.00	1.00	.1982	.39864	1.514
2000	T_4	777408	.00	1.00	.2047	.40348	1.464
2001	T_5	777408	.00	1.00	.1628	.36917	1.827
Socio-economic and demographic contextual conditions of vehicle owners measured at census block-group level of vehicle owners' geo-coded addresses							
Median household income ($)	W_1	519416	.00	200001.00	59836.824	25739.8725	1.408
Per capita income ($)	W_2	519416	.00	120932.00	27679.681	13973.8174	2.231
Median home value ($)	W_3	519416	.00	914800.00	163263.164	102789.2268	2.649
% Employed	W_4	519416	.00	94.9	67.859	9.5147	-1.432
% White	W_5	519416	.00	100.00	65.281	30.6740	-.897
% Black	W_6	519416	.00	100.00	26.504	30.6491	1.242
% Hispanic	W_7	519416	.00	83.60	6.107	9.3910	3.285
% Asian	W_8	519416	.00	39.20	3.480	4.4745	1.998
% Other races	W_9	519416	.00	62.10	2.926	4.9218	3.787
% male	W_{10}	519416	.00	99.70	49.160	4.1050	.325
% female	W_{11}	519416	.00	94.60	50.820	4.1091	-1.045
% age 18-24	W_{12}	519416	.00	98.60	8.833	5.3475	4.346
% age 25-34	W_{13}	519416	.00	60.80	17.700	8.4881	1.101
% age 35-44	W_{14}	519416	.00	46.20	18.199	4.0068	-.046
% age 45-54	W_{15}	519416	.00	34.10	13.930	4.4618	.482
% age 55-64	W_{16}	519416	.00	32.50	7.712	3.5455	.932
% age 65 +	W_{17}	519416	.00	100.00	8.158	6.1354	3.428

Table 5.1 shows descriptive statistics of the mixed-pool remotely sensed sample data collected between 1997 and 2001. Annual distribution of the remotely sensed sample data can be elicited from the mean values of five temporal variables: 1997 [T_1], 1998 [T_2], 1999 [T_3], 2000 [T_4] and 2001 [T_5]. 25.07% of the sample was observed in 1997, 18.36% in 1998, 19.82% in 1999, 20.47% in 2000 and 16.28% in 2001. This shows that the sample is collected almost evenly for each year in the study period.

Figure 5.2 shows 73 remote sensing sites that were used to collect the sample data between 1997 and 2001. This figure shows that remote sensing data has been collected inside the 13 IM program counties during the five years of the study period. Figure 5.2 also shows % of observations as a part of total sample collected at each remote sensing site from 1997 to 2001. This map shows that majority of the remote sensing sites are located in the four-county area of Fulton, Dekalb, Gwinnent and Cobb (where both the basic and enhanced IM program has been implemented), and more than two-third observations of the total sample were collected there. The selection of a remote sensing site is an extremely important design parameter in this research. Though ideally remote sensing data should be collected on every road of the Atlanta MSA, this is neither feasible nor technologically possible. Remote sensing sites can only be chosen where traffic flows in single lanes. The majority of the remote sensing sites are located at entrances to major interstates/high-ways or their exits. Data from surface roads and smaller arterial roads is, however, also available in the sample, which is mostly collected in Atlanta city's outskirts.

In 1997, the remote sensing data was collected for 21 days spread over all the year. Similarly, the 1998 data was collected on 15 days, 1999 and 2000 data on 18 days, and 2001 data on 17 days. Furthermore, hourly sampling time in all years of the sample data was between 6 am in the morning and 6 pm in the evening. Ideally, the data should be collected on each of the 365 days of a year and 24 hours of a day. Data collection costs, however, do not permit meeting this ideal.

Five remote sensing instruments were used by AQL to collect the sample data. 2 of these 5 instruments are known as "first generation smogdog devices" (FG-SMD), while the remaining three instruments are known as "second-generation remote sensing devices" (SG-RSD). FG-SMD were used between 1997 and 2000 while SG-RSD were used between 1999 and 2001. FG-SMD data (1997-2000) measures CO and HC emissions concentrations, but, unfortunately, the first generation SMD data do not

contain variables measuring NOx, speed and acceleration of the vehicles. AQL started collecting the remote sensing data through second-generation RSD instruments in 1999. The second-generation RSD data (1999-2001) contains variables measuring CO, HC, NOx, speed and acceleration of the vehicles. This research uses both FG-SMD and SG-RSD data to enhance the temporal coverage and sample size of the study. A variable "generation of remote sensing instrument" [S_7] is coded zero for observations collected by first generation instruments and 1 for 2nd generation instruments. This variable is included in the regression models to minimize the instrumentation effects in measuring the vehicular tail-pipe emissions.

5.4 Variable operationalization and database construction

5.4.1: Vehicular characteristics:

Vehicles in the sample are classified according to the following characteristics:[86] vehicle age (observation year minus model year) [R_1], vehicle type [R_2], vehicle manufacturer [R_3 to R_{15}][87], country of vehicle manufacturing [R_{16} to R_{24}] and emission-control technology type [R_{25} to R_{31}]. Descriptive statistics on these variables [R_1 to R_{31}] are presented in table 5.1. These vehicle characteristics, among others, are included in the CAFÉ data released by AQL; and are primarily ascertained either through matching the RSD observed license plates with the license plates in the vehicle registration databases, or through decoding the VIN of a vehicle.

Vehicle Registration data, provided by Georgia Department of Motor Vehicles (GA-DMV), captures the registration patterns of vehicles in the state of Georgia from 1997 to 2002. The key variables of interest are the VIN, the model year, the make and model name of the vehicle, the date of registration, the address of registration, and, only in 1998 and 1999 data, the vehicle registration expiration date and the birthday of the vehicle owner (which is the same for the day and month arguments of both variables). This database changes every day as vehicles migrate in and out of Georgia, or new vehicles get registered and old ones scrapped. AQL does not have access to registration data for each day; rather, data on a tri-monthly basis is provided. The remote sensing

---

[86] In addition, data on vehicle make and model is also available but it is not included in the analysis to reduce complexity. Further, fuel type is another important characteristic of vehicles in the sample but is not included in the analysis because IM program only targets gasoline-fueled vehicles. Non-gasoline vehicles (such as diesels and electrics) constitute less than 0.5% of the sample and are included in the following fleet types: in-eligible fleet, rest-of-Georgia fleet.
[87] Data on vehicle manufacturers for the year 1998 is not currently available.
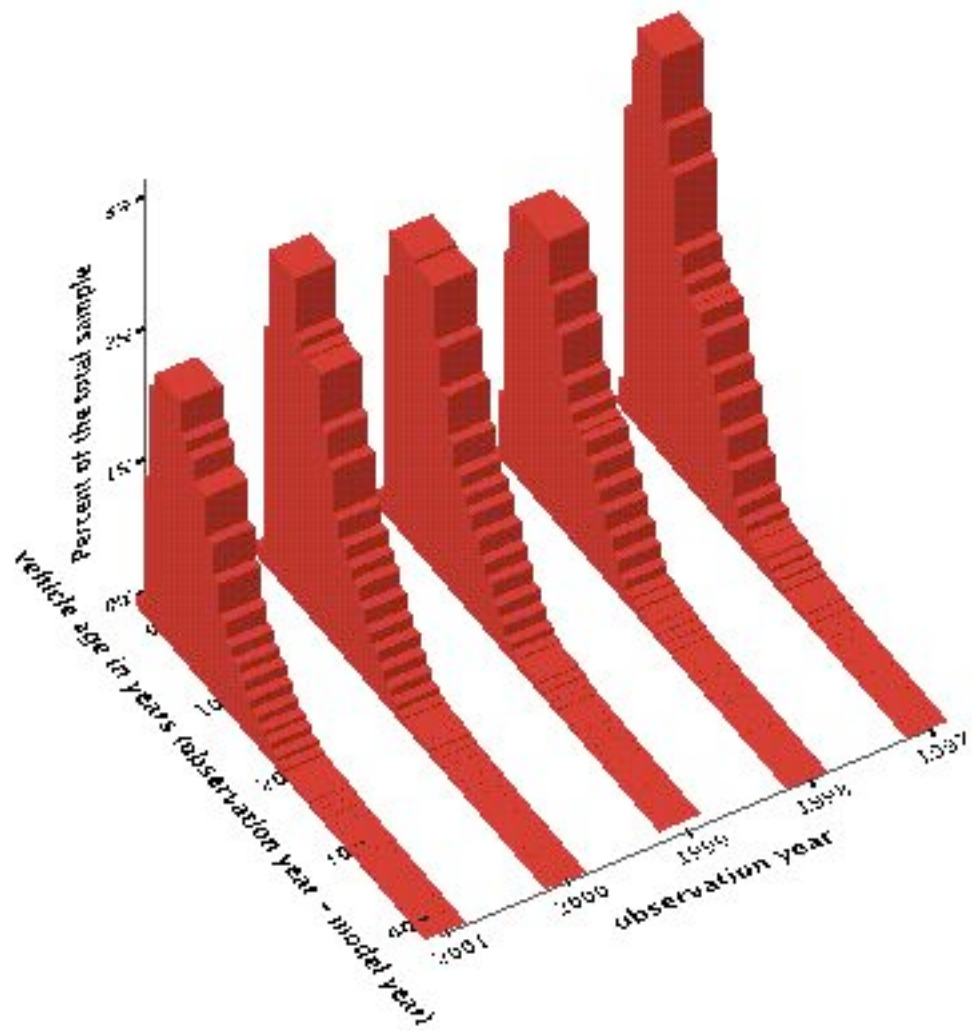
Figure 5.3: The remote sensing sample distributed by vehicle age and observation year
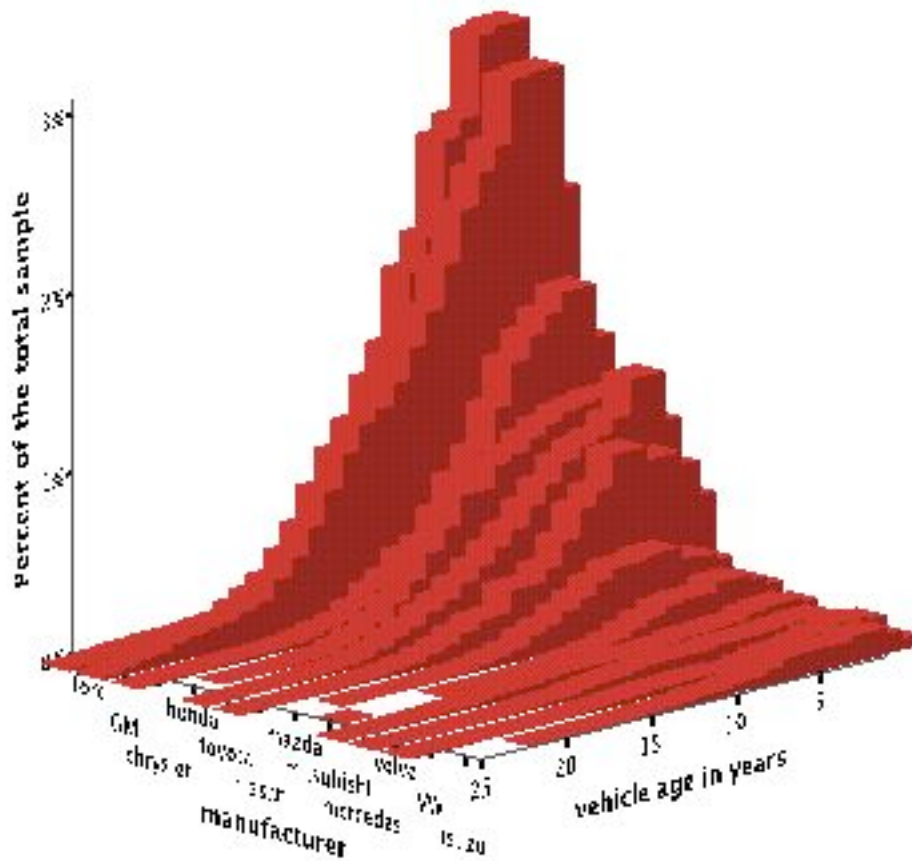
Figure 5.4: The remote sensing sample distributed by vehicle age and vehicle manufacturer.

sample for each year is matched with the 4 vehicle registration databases of that year to get information about the variables of interest.

Table 5.1 shows that mean age of the vehicles in the sample is 5.4 years. Distribution of the sample by vehicle age and observation year is presented in figure 5.3. 62% of the total sample contains passenger cars, while the remaining 38% contains trucks, vans, mini-vans and SUVs.

Descriptive statistics in table 5.1 show that 16.94% of the vehicles in the sample were manufactured by Ford, 19.74% by GM, 8.78% by Chrysler, 7.85% by Honda, 7.27% by Toyota, 5.54% by Nissan, 2.57% by Mazda, 1.24% by Mitsubishi, 1.10% by

Mercedes, 1% by Volvo, 0.76% by VW and 0.82% by Isuzu. Vehicle manufacturer information about 18.36% of the sample observed in 1998 is not available, while other manufacturers (such as BMW, Rolls Royce, etc.) produced the remaining 8.03% of the total sample. The variable, other manufacturers, represents 26.39% of the sample, which includes 18.36% missing information. Figure 5.4 shows distribution of the sample by manufacturer and vehicle age.

As shown in table 5.1, 60.69% of the sample represents USA as the country of the vehicle manufacturing (or country of the final assembly), while Japan is the second highest at 15.94%, Canada at 9.52%, Germany at 2.98%, Mexico at 2.34%, Sweden at 1.5%, Korea at 0.89%, UK at 0.39% and other countries at 5.79%.

Table 5.1 shows that 25% of the total remote sensing sample vehicles are equipped with AIR, 96% with TWC, 82% with EGR, 97% with CLL, 14% with TAC, 3% with OXY and almost 100 % with PCV emission control systems. Seven emission control technologies are distributed more or less similarly in all the five years of observation, except that AIR seems to decline from about 7% in the 1997 sample to less than 4% in the 2001 sample and TAC from about 5% to 2.5% during the same period.

While mileage of a vehicle is theoretically a strong explanatory variable of changes in vehicular emissions, it is extremely unfortunate that the odometer data in the vehicle registration database is poorly reported. Due to the lack of reliability, the variable odometer as measured in the registration databases is dropped. At the time of aggregating the Atlanta fleet-wide emissions in terms of mass emission rates, a VMT-based methodology is used, which is explained in Appendix A. The VMT-based methodology uses more reliable but aggregate mileage data, as released by BTS, US-DOT for the state of Georgia for the study period. Dropping the vehicle level odometer data causes potential omitted variable bias in predicting on-road vehicular tailpipe emissions, which is a major limitation of this research design.

5.4.2: Contextual conditions at the time of measurement:

As shown in table 5.1, road grade at remote sensing measurement sites varied from –6.00 degrees (i.e. 6 degrees downhill slop) to 7.50 degrees (i.e. 7.5 degrees uphill slop). The mean gradient at the remote sensing sites is 0.77 degrees. The sine of road-grade measures the vertical axis of the angle of slope of the road, which is used in regression models. Speed and acceleration of the vehicles was directly measured by the second-generation remote sensors only. For the sample values of the first generation

remote sensors, the missing values are filled by estimating average speed and acceleration for each remote sensing site. For the overall sample, as shown in table 5.1, vehicles were measured traveling between the minimum speed of 0.30 MPH to a maximum of 74.60 MPH. The sample mean is 37.72 MPH. The sample vehicles were decelerating up to 13.30 MPH/Second and accelerating up to 13.30 MPH/second at the time of observation. The sample mean stands at acceleration of 0.71 MPH/second.

The atmospheric variables – temperature, humidity and pressure – were estimated for each day and hour of observation by linking the sample data with the Local Climatological data (1997 to 2001) released by National Climatic Data Center (NCDC), National Oceanic and Atmospheric Administration (NOAA). The climate data contains three-hourly observations of meteorological variables measured at NCDC weather station in Hartsfield International Airport, Fulton County, Atlanta. The three-hourly climate data observations are used to impute one-hourly observations for each day of the remote sensing data collection (a total of 89 days in five years) by estimating a linear trend at a point. There are two trends obvious in 89 days (spread over five years) of the sample: First, temperature in Atlanta is cooler in the winter months, milder in spring and fall, and hotter in summer months. Second, almost every day of observation, temperature was lower in the morning hours, rose by the afternoon to the day's peak, and then started to decline after 5 pm. Similarly, there are two trends common in the relative humidity data: First, Atlanta is a relatively humid place (with sample mean of 59.31%). Second, humidity is normally higher in the early morning hours, declines by afternoon and then starts to rise again by later afternoon. There are quite a few exceptions to the normal trend, with some days of observation having 100% humidity and others consistently less than 40%. The atmospheric pressure is also estimated for each hour and day of observation. As shown in table 5.1, pressure ranges from 28.49 minimum to 30.22 maximum and a mean of 29.01 inches of Mercury at the Atlanta Hartsfield International Airport for 89 days of observation.

5.4.3: Fleet types as decision variables:

As described in section 1.3, and shown in the terminal nodes of figure 1.3, 11 fleet types of the vehicles in the sample, which reflect the cooperative and non-cooperative decisions taken by vehicle owners in response to the regulatory IM program intervention in the Atlanta airshed, are estimated. This is essentially accomplished by tracking the IM testing records of the remotely sensed sampled vehicles. Inspection and

Maintenance (IM) and exemption data (1997-2001) is provided by Georgia Department of Natural Resources (Ga-DNR), Georgia Environmental Protection Division (Ga-EPD). The IM database contains about one to two million observations of vehicles tested each year, depending upon the rule regime of the IM program as explained in section 4.3. The key variables in the IM database are the time and place of the IM test, the measurement levels of CO, HC and NOx, the VIN, the model year, make and technology type of the vehicle and, most importantly, the test-type (i.e. initial or re-test) and over-all test results (i.e. fail or pass). The IM exemption data provides information about the VIN and model year of the vehicles that were exempted from the IM test.

11 fleet type variables for each *annual sample* were coded. The annual samples are used at this stage because it facilitates their matching with IM program data and lets us track the changes in the IM program rules from year to year. Table 5.1 presents the summary sample statistics for 11 fleet types. The remote sensing sample between 1997 and 2001 contains on average 27.01% vehicles in the control fleet [initial test initial pass], 52.13% vehicles in the IM in-eligible fleet, 0.23% vehicles in the waived fleet, 10.18% vehicles in the rest of Georgia fleet and 3.78% vehicles in the missing fleet. The five fleets mentioned in the preceding sentence serve as multiple control groups in this research design. The remaining six fleets are categorizations of vehicles in different treatment groups; the cooperative fleets include vehicles in retest pass and migrated pass fleets, while non-cooperative fleets include vehicles in retest fail, migrated fail, missing fail and missing pass groups.[88] Table 5.1 shows that the retest pass fleet contains 1.89% vehicles of the total sample and the migrated pass fleet contains 0.86% vehicles. The sample mean for retest fail vehicles is 0.37%, migrated fail vehicles is 0.11%, missing fail vehicles is 0.33% and missing pass vehicles is 3.14%.

Figure 5.5 shows the remote sensing sample distribution by fleet type and observation year. Due to the IM program shift from a biennial program to an annual program in 2001, it is noticeable in figure 5.5 that the ineligible fleet is drastically reduced

---

[88] Due to the non-discernable changes in vehicle ownership, it is difficult to decide whether vehicles in missing pass fleet are cooperative or non-cooperative. I designate them non-cooperative because these vehicles were required by IM program rules to appear in IM test, but they are missing from IM testing records. I do not include them in the missing fleet because they have been found to have IM test records in the previous IM cycle, in which they passed the initial test. The designation of missing pass fleet as non-cooperative fleet is based on the assumption that the vehicle owners observed on-road are the same as at the time of vehicle's last IM test in the previous year/cycle. This assumption needs to be tested.
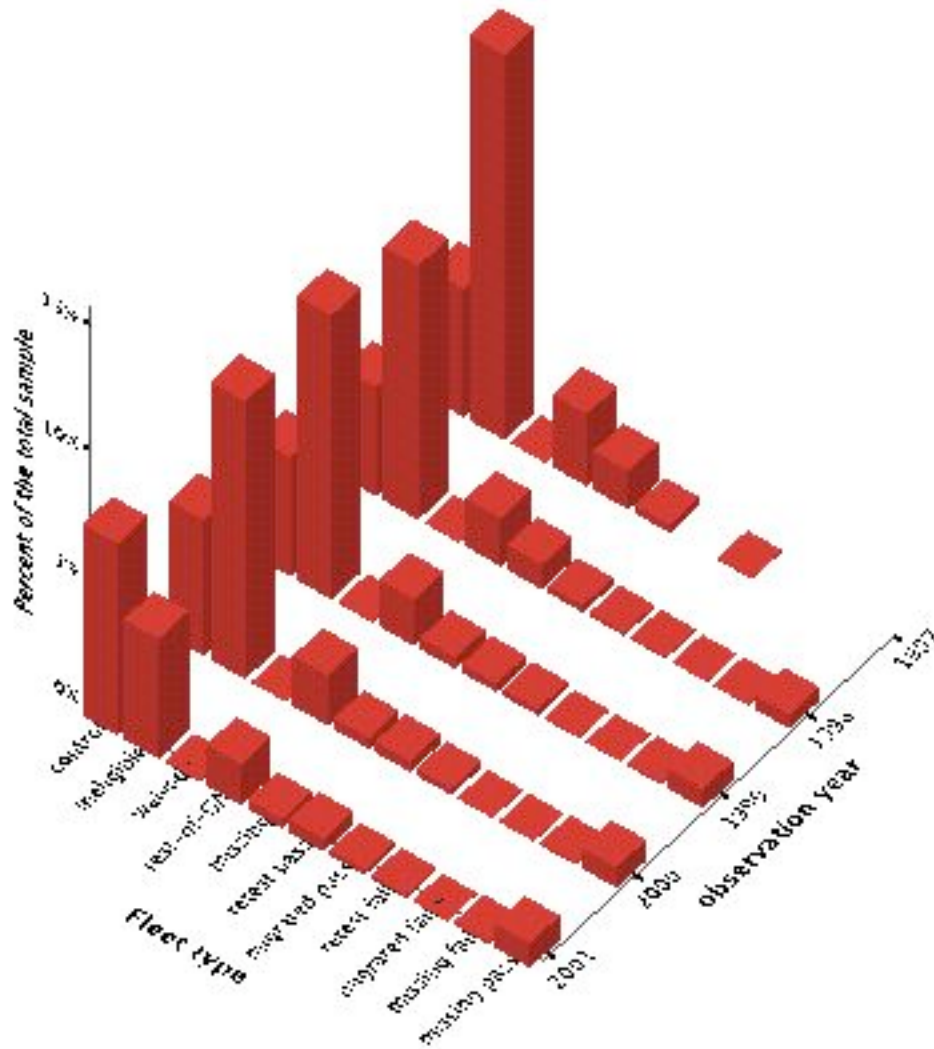
Figure 5.5: The remote sensing sample distributed by 11 fleet types and observation year

in 200_   _sed.
Notice _____ due
to this change of rule, which is interesting because it suggests that the behavioral
parameters ascertained through the remote sensing data are robust and generalizable.
The majority control group of vehicles are relatively younger in age, though older

vehicles are also initial test initial passes. More importantly, cooperative and non-cooperative vehicles belong in all vehicle age groups, and not just older vehicles.

5.4.4: Tail-pipe vehicular emissions:

Table 5.1 shows that the mean CO emissions of the sample in concentration units are 0.4796%, mean HC emissions are 180 PPM and mean NO emissions are 522 PPM. Converted as emission factors, as described in appendix A, mean CO, HC and NO emissions for the sample stand at respectively 213 gg^{-1}, 18.65 gg^{-1} and 24.73 gg^{-1}. Figure 5.6 shows vehicular tail-pipe emissions distributed by vehicle age and observation year. Panel A in figure 5.6 shows CO distribution and indicates that CO vehicle emissions are an increasing function of vehicle age, and as vehicle age increases above 14 years, the standard error also increases. Panel A also shows that CO emissions are decreasing for each year of the sample, while holding vehicle age constant. Panel B in figure 5.6 shows mean HC emissions by vehicle age and observation year. Panel B shows that HC emissions also increase by vehicle age; their uncertainty interval also rises after vehicles are 10 years or older. HC emissions also appear to have decreased significantly from their 1997 sample level to 2001 level, while holding vehicle age constant. Panel C shows NO emissions as a function of vehicle age and observation year. NO emissions increase exponentially up to the age of 15 years and then appear to decrease at a lower slope. The standard errors also increase significantly after 15 years of vehicle age. The NO emissions by observation year, holding vehicle age constant, show confounding sample statistics. While emissions appear to decrease from 2000 to 2001, it appears that NO increased from 1999 to 2000. This confounding result may be due to smaller sample size in 1999 second generation data, which is only 1.075% of the total sample. It is also possible that NO emissions actually increased from 1999 levels to 2000 levels, while holding vehicle age constant. Mean NO emissions in 2001, however, appear to be lower than both 1999 and 2000 levels.

Figure 5.7 shows the annual trend of CO, HC and NO emission factors by 11 fleet types during the study period 1997 to 2001. While CO, HC and NO emission factors have decreased from 1997 to 2001, the vehicles in the five experimental fleets –retest pass, migrated pass, retest fail, migrated fail, and missing fail –emit higher CO, HC and NO emissions than the control group vehicles. Only the missing passed fleet of vehicles emits similar emissions as the control group vehicles. Vehicles in the ineligible

Figure 5.6, Panel A: CO

Figure 5.6, Panel B: HC

125

Figure 5.6, Panel C: NO
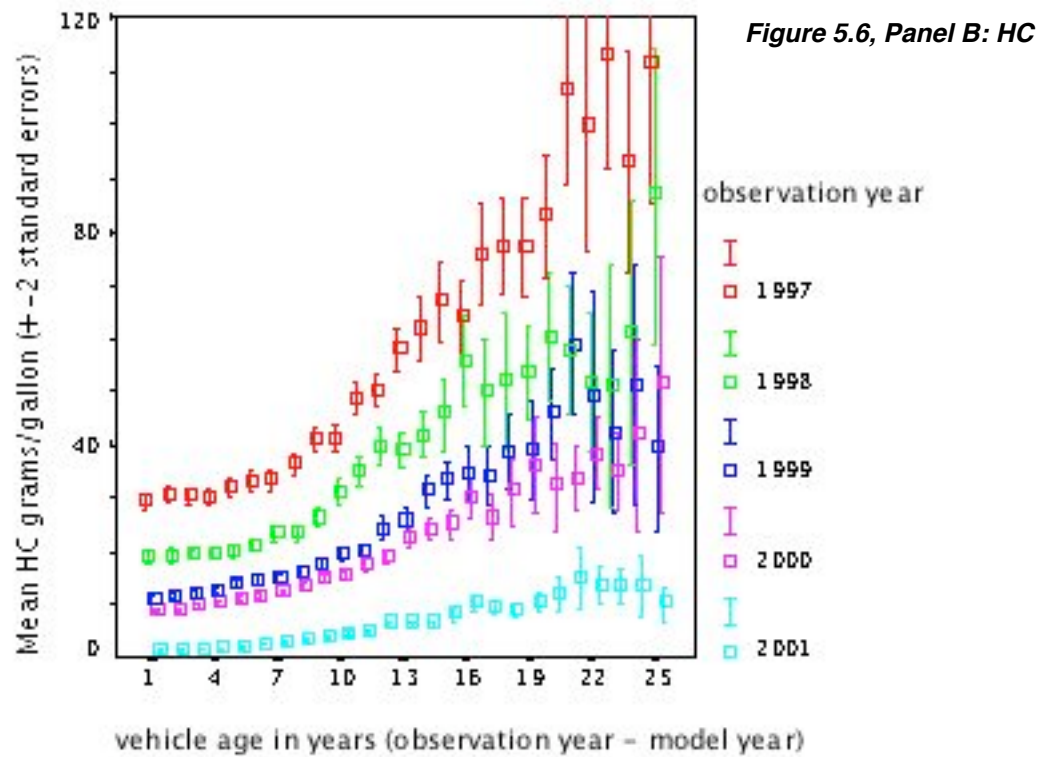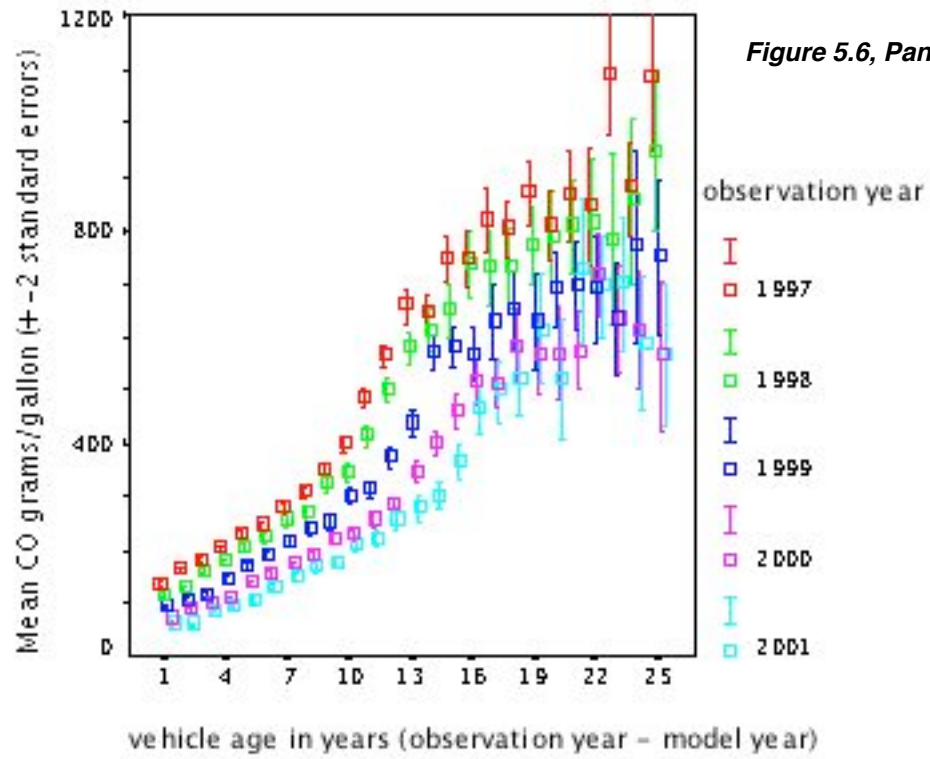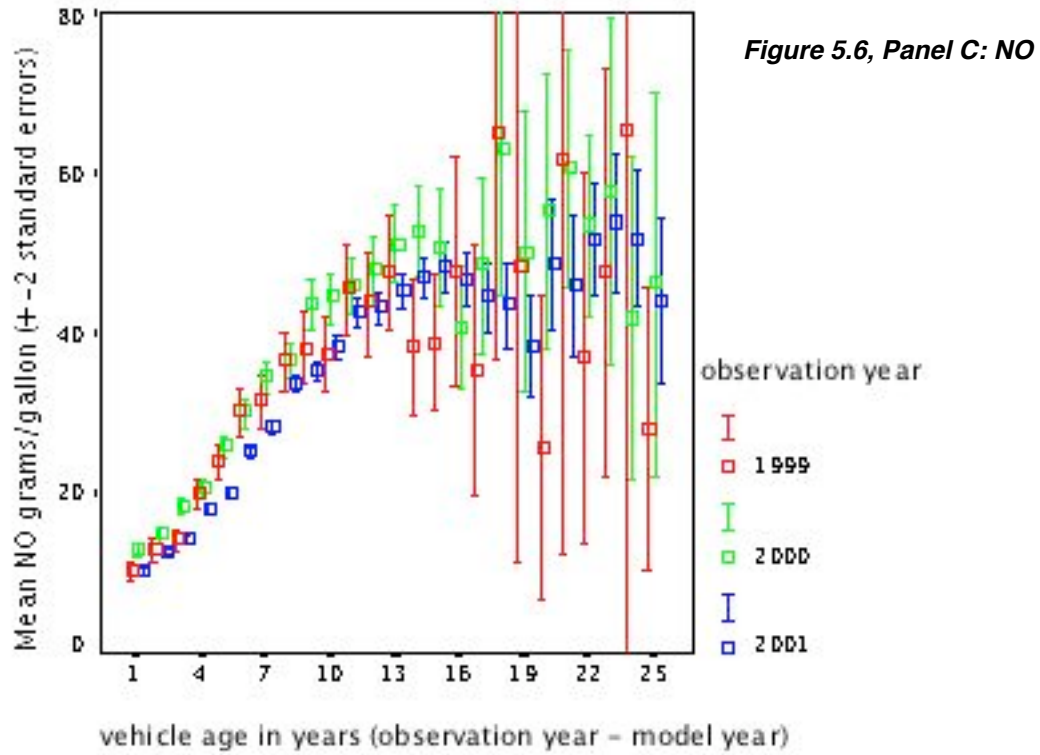
Figure 5.6: Vehicular tail-pipe emissions of CO, HC and NO distributed by vehicle age and observation year

126
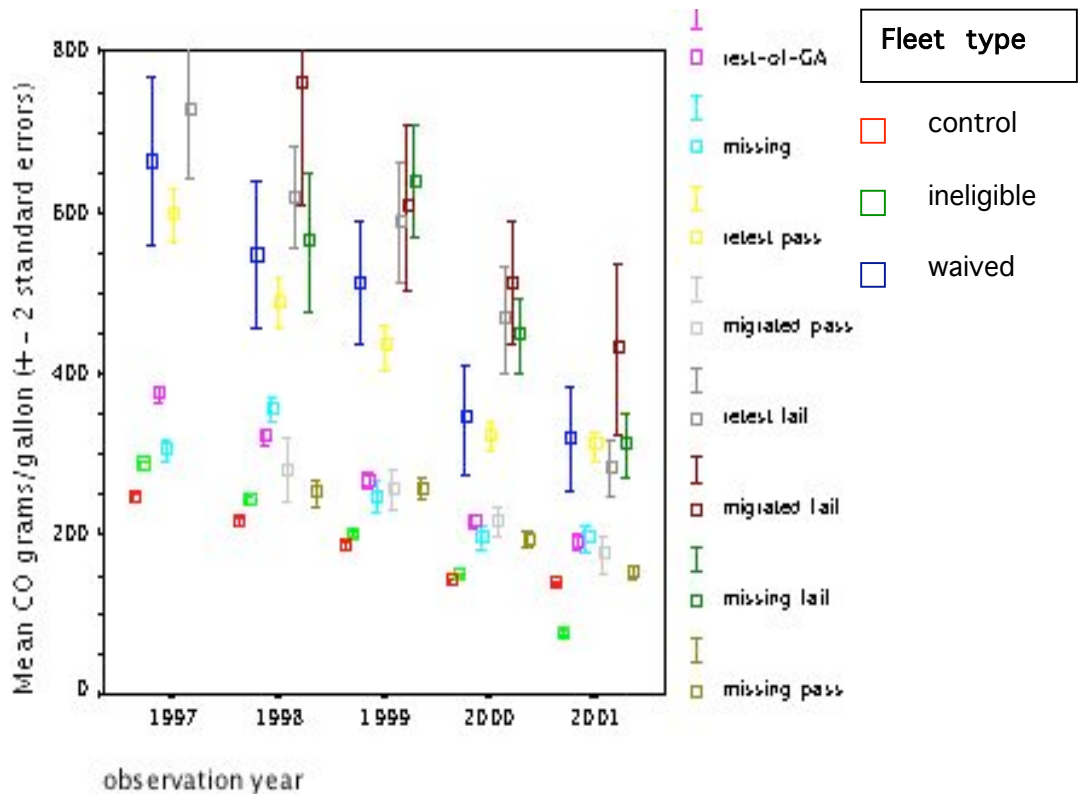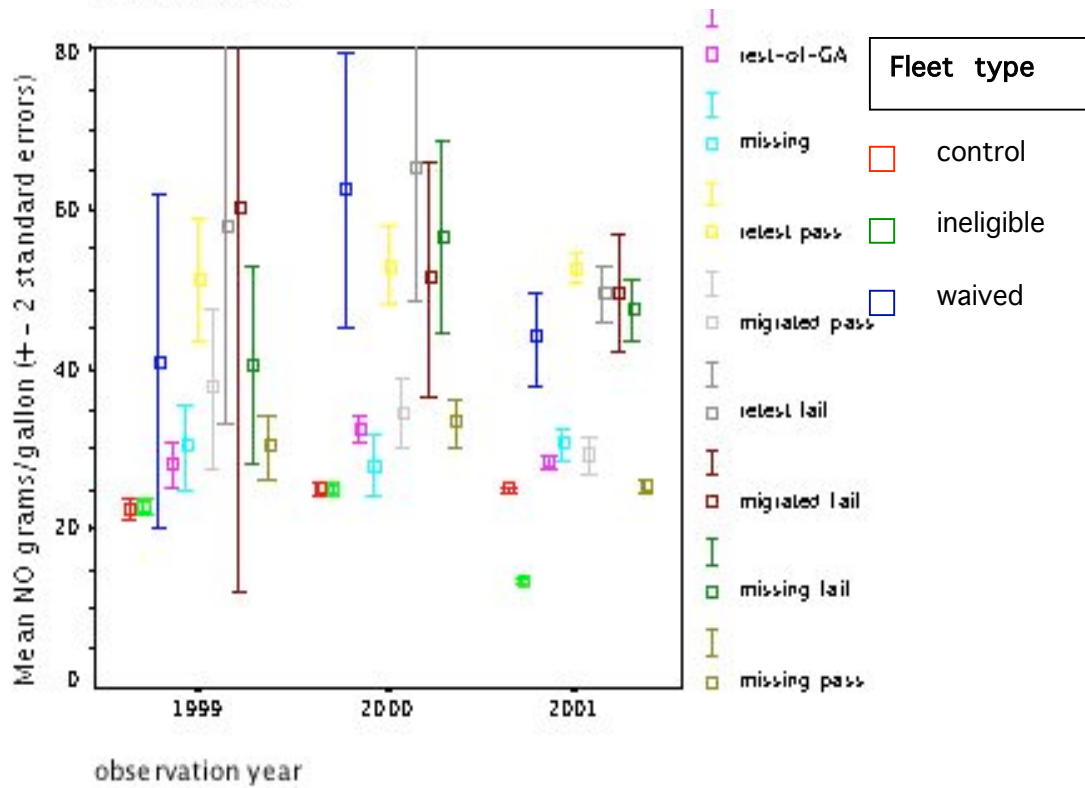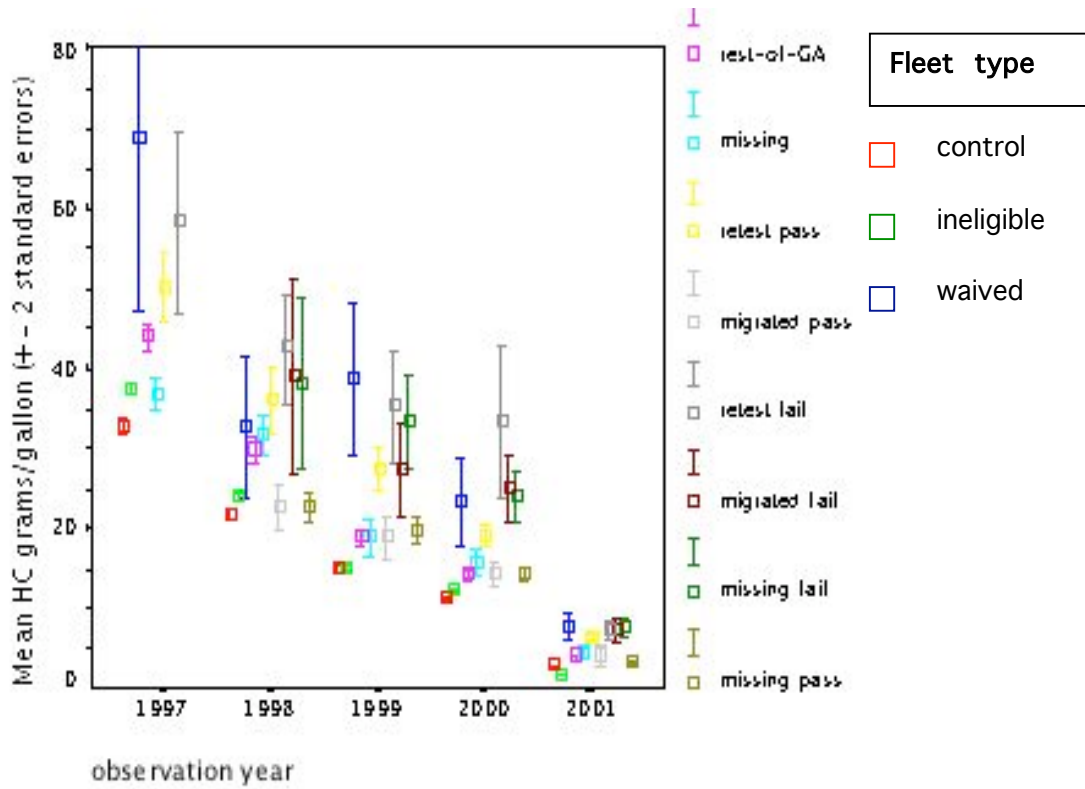
Figure 5.7: Annual trend of CO, HC and NO emission factors by 11 fleet types

127
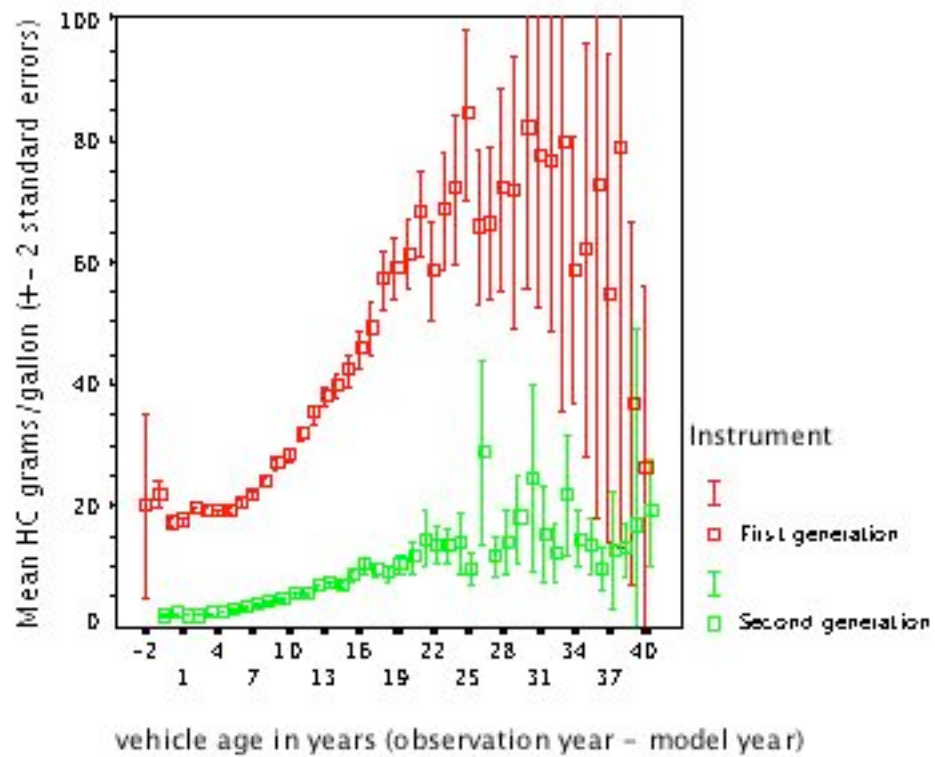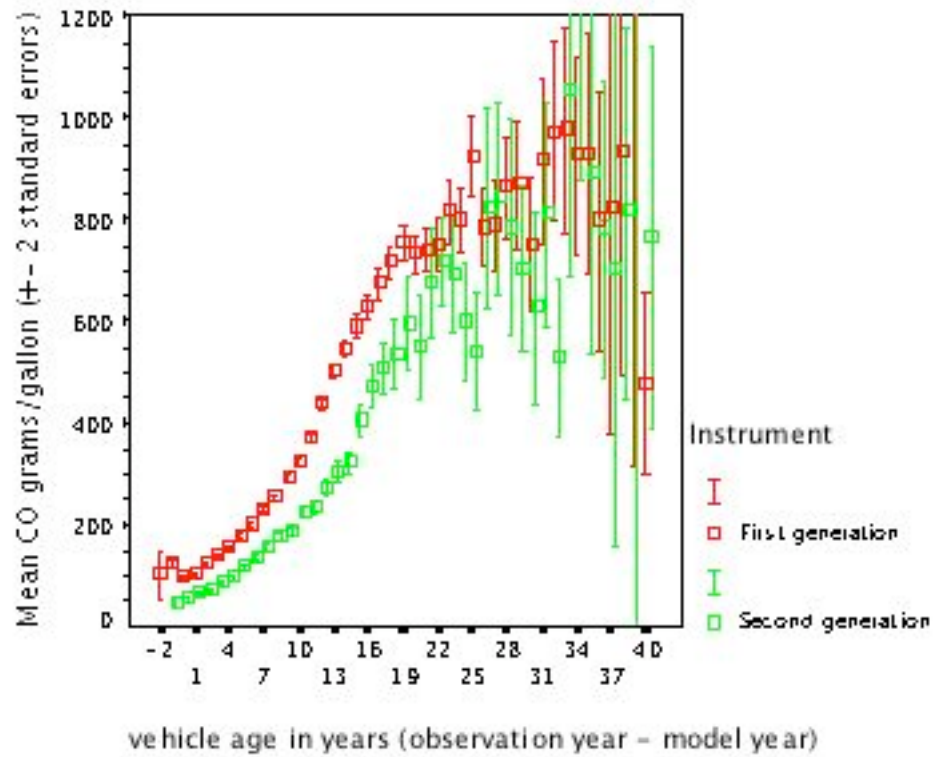
Figure 5.8: The effects of remote sensing instrument-generations on mean CO and HC emissions in the sample

fleet are also similar to the control group, but the waived group vehicles emit on average higher emissions than the control group vehicles.

78% of the sample was collected by first generation instruments [nos. 1 and 2] between 1997 and 2000, while 22% was collected by second generation instruments [nos. 418, 503, 511] between 1999 and 2001. While pooling together the data measured by these five instruments of two different generations, it is important to be cautious about the instrumentation effects of the quasi-experimental research design. Figure 5.8 shows that CO and HC emissions measured by first and second generation instruments differ significantly from each other, with second generation instruments measuring consistently less CO and HC emissions, while holding vehicle age constant in the sample. NO emissions were only measured by three second-generation instruments. This is a very confounding picture for CO and HC emissions because the instrumentation effects are interacting with other covariates, especially the observation year/temporal effects. A better way to capture the instrumentation effects is by comparing the instruments of the two generations for same observation years [i.e. 1999 and 2000], which is done in the regression models. In order to take account of the instrumentation effects, the variable "generation of remote sensing instrument" is therefore included in the regression models.

5.4.5: Socio-economic and demographic contextual conditions of vehicle owners:

Census data (2000) released by US census bureau, and formatted by Geolytics Inc., captures demographic and socio-economic patterns.[89] This study uses census block-group ecological level data for the state of Georgia. The addresses of vehicle owners tracked in vehicle registration data are geo-coded at the census block-group level to access various socio-economic and demographic contextual conditions of the vehicle owners. In particular, the following variables, which are broadly grouped in three categories, are of special interest [as explained in section 1.4]. (1) Economic variables: the median household income [W_1]; the per capita income [W_2]; the median home value [W_3]; % employed [W_4]. (2) Social variables: % of white population [W_5], % of black population [W_6], % of Hispanic population [W_7], % of Asian population [W_8], % of other races' population (such as native Americans, pacific Americans) [W_9]. (3) Demographic variables: % of male population [W_{10}], % of female population [W_{11}], % of population

---

[89] The 2000 census data is available from Geolytics at www.geolytics.com. Geolytics extracted this data from SF1, SF2 and SF3 files released by US census bureau (www.census.gov).

between the ages of 18 and 24 years [W_{12}], % of population between the ages of 25 and 34 years [W_{13}], % of population between the ages of 35 and 44 years [W_{14}], % of population between the ages of 45 and 54 years [W_{15}], % of population between the ages of 55 and 65 years [W_{16}], and % of population 65 years and above [W_{17}].

66.8% of the remote sensing sample was successfully geo-coded, which affects the randomness of the mixed pool sample.[90] More importantly, GA-DMVS introduced higher reporting standards and validity tests in the vehicle registration data since June of 1999 (which they call GRATIS data), and it is noticeable that the successful geo-coding rate for 1997 and 1998 sample is relatively lower (52.46% and 59.93% respectively), while for GRATIS data of 1999, 2000 and 2001 is relatively higher (72.84%, 76.57% and 77.08% respectively).

Table 5.1 shows descriptive statistics of economic, social and demographic variables for the geo-coded sample. The mean of the median household income in the block-groups of sampled drivers stands at $ 59,836.82, while mean per capita income is $27,679.68. On average 67.8% of the population in drivers' block-groups were employed, and mean of the median home value stood at $163,263.16.

Figure 5.9 shows median household income distribution in the sample: Panel A plots income versus vehicle age; and, as expected, income decreases as vehicle age increases. Panel B plots income as distributed by vehicle age in clusters of control and treatment vehicle groups. Vehicles of all ages in the treatment group are owned by relatively poor people as compared to the control group. Panel C plots income for control and treatment groups of vehicle owners in each of the five years of data observation. Vehicle owners in the treatment groups come from relatively poorer areas in all five years of observation as compared to the control group vehicle owners. Panel D shows that the migrated fail group of vehicle owners is the poorest, followed by migrated pass,

---

[90] Out of 777,408 observations in the mixed pooled sample, 519,416 (66.8%) vehicles were geo-coded and 257,992 (33.2%) were not geo-coded. There is always a trade-off between the criteria of "accuracy" and the "coverage" in successfully geo-coding the addresses. Accuracy at 80% (and above) was chosen for this study, which sacrificed higher coverage of geo-coded sample. If the accuracy is reduced to 50%, the geo-coding rate increases from 66.8% to 78%. Due to the large sample size available for this study, accuracy was chosen over coverage. In turn, the t-tests show that the geo-coded sample is slightly different from the non-geo-coded sample. While CO and HC emission concentrations are slightly higher for non-geo-coded sample observations, NO is same for both geo-coded and non-geo-coded samples. Of the six treatment vehicle groups, retest fail, migrated fail and migrated pass means are the same for both geo-coded and non-geo-coded samples, while retest pass, missing pass and missing fail means are slightly higher for geo-coded sample.
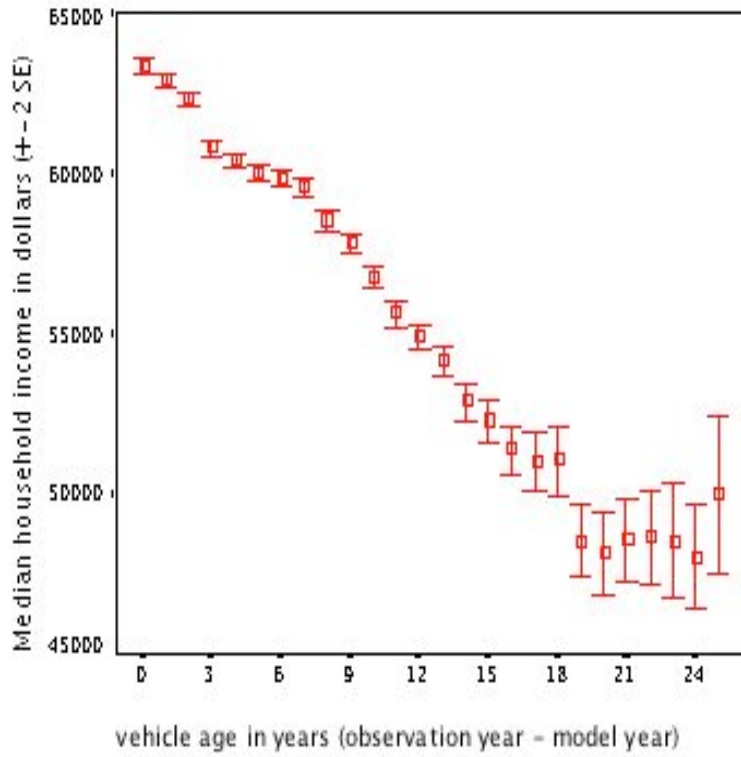
Figure 5.9, Panel A

Figure 5.9, Panel B

131
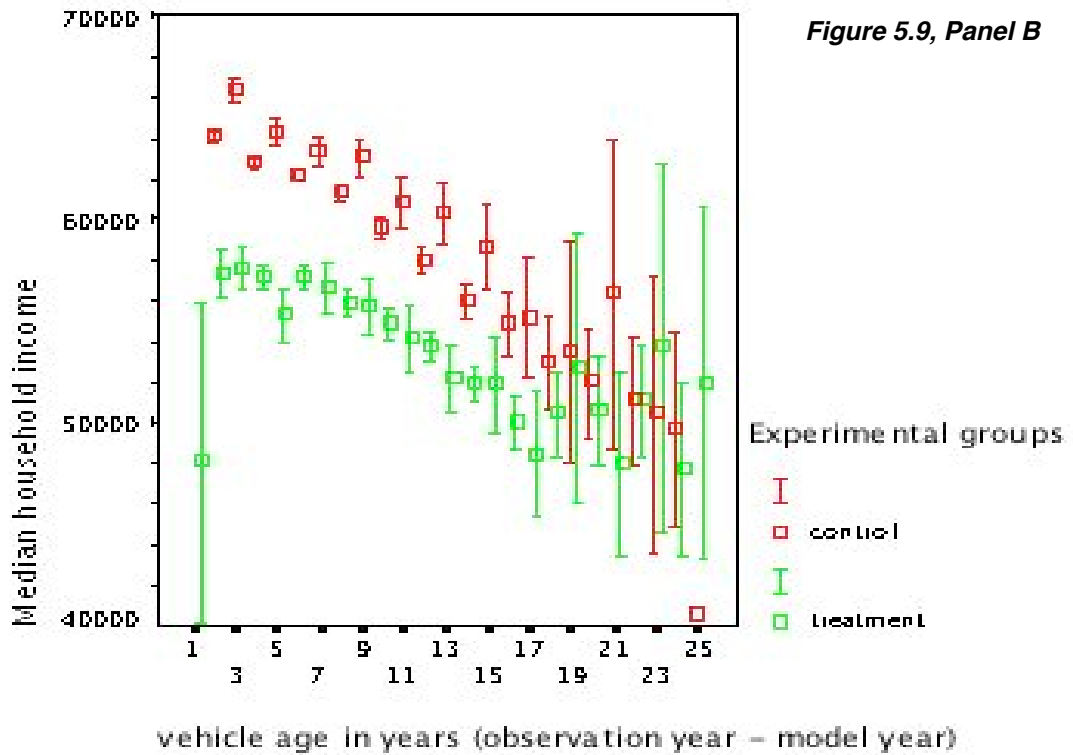
Figure 5.9, Panel C
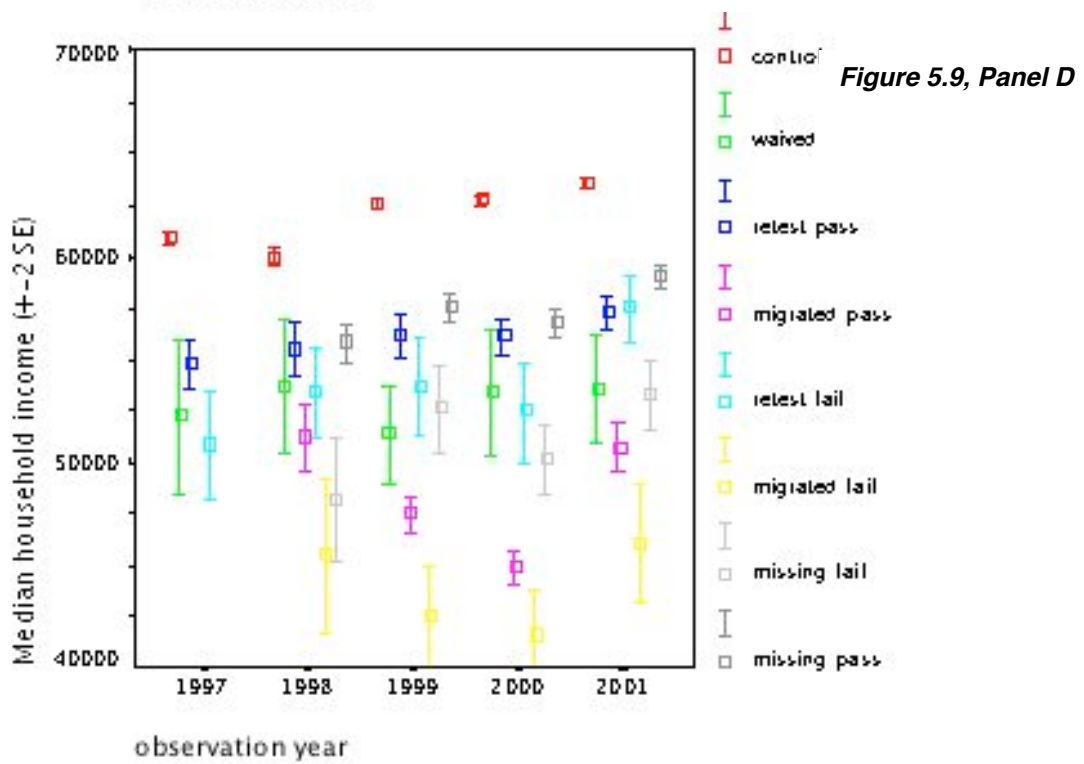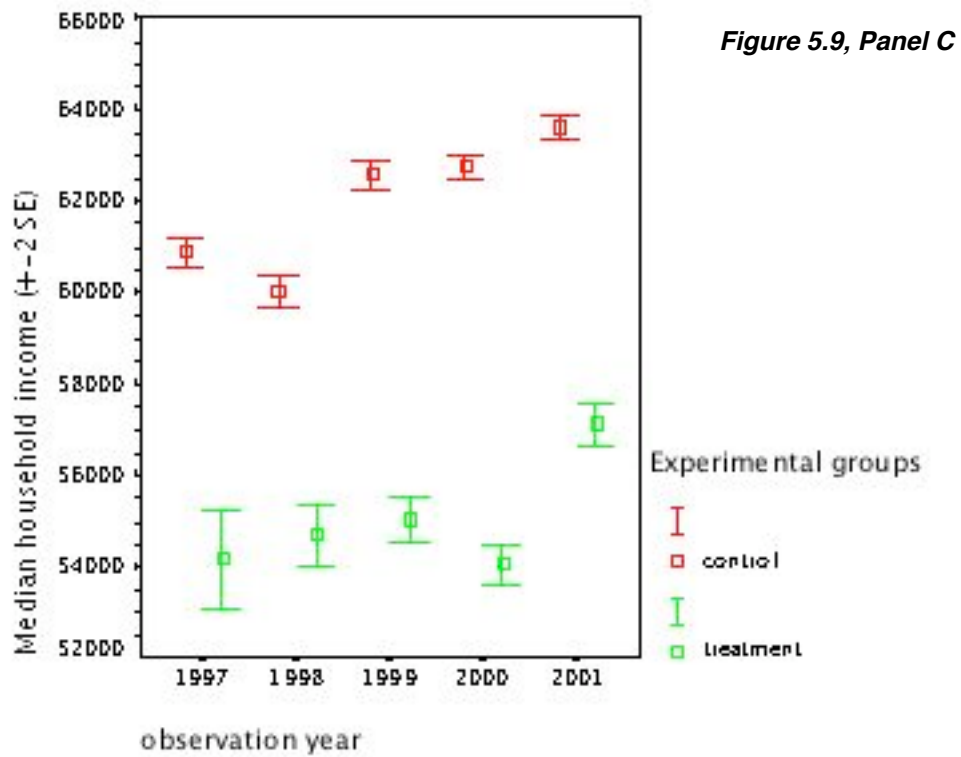
Figure 5.9, Panel D

Figure 5.9: Median household income in blockgroups of vehicle owners' addresses distributed by vehicle age (panel a), experimental groups (panel b), observation year (panel c), and vehicle groups (panel d)

missing fail and retest fail groups. Note that vehicle owners in the retest pass groups appear to be slightly richer than the ones in retest fail group.

5.5 Data analysis methodology

5.5.1 The probability of cooperative and non-cooperative decision behaviors of high-emitting vehicle owners in the Atlanta airshed

As the bold-faced terminal nodes in figure 1.3 show, and as explained in section 1.3, the sample of the on-road data that is selected for a given year is subdivided into 11 vehicle fleets: (a) 5 groups may be considered as separate control groups that includes control (initial test initial pass), IM ineligible inside 13 county area, waived, rest of Georgia and missing fleets. (b) 2 groups may be considered as cooperative fleet types, which include retest-pass, and migrated pass groups. (c) 4 groups may be considered as non-cooperative fleet types, which include retest-fail, migrated fail, missing fail and missing pass fleets.

These three broad classifications have severe limitations, the most important of which are the following: (1) the control (initial test initial pass) group of vehicles includes vehicle owners who pre-emptively repaired emission control systems of their vehicles before appearing in the initial IM test in a given year. This would include non-cooperative vehicles (path no. 23 in table 1.1) if vehicle owners carried out fraudulent repairs; and cooperative vehicles (path no. 12 in table 1.1) if vehicle owners carried out actual repairs. (2) The migrated pass group of vehicle owners may be acting to preemptively avoid the IM program by registering their vehicles outside the IM program area, but note that they are observed driving inside the IM program area. (3) The missing pass group of vehicle owners includes those who sold their vehicles after passing the IM test to other vehicle owners inside the IM program area (which may cause them to miss the IM test due to different birthdays of vehicle owners), for which reason not all of them can be classified as non-cooperative types. On the other hand, the missing pass group, by definition, is a non-cooperative type, because as per IM rules they were eligible to appear in the IM test, but their VIN records are not found in the IM data of the evaluation year. (4) The three classifications do not estimate the extent of vehicles that simply avoid registration inside the state of Georgia and are still driven inside the IM program boundaries without valid license plates. (5) These classifications do not capture the vehicles that are registered out of the state of Georgia, such as Alabama or Tennessee, but are still driven inside the Atlanta IM program boundaries. (6) Both IM and remote

sensing data methodologies contain the possibility of a matching error due to the incorrectly reported VIN and model year variables. This matching error is probably represented in the category of "missing fleet" vehicles, but this is not certain.

Given these six serious limitations, utmost caution is needed to interpret the statistics that reduce 11 fleet types to 3: control, cooperative and non-cooperative. Due to these limitations, the empirical results for all eleven fleet kinds are reported. On the other hand, the theoretical underpinnings in decision theory require a reduction of the 11 fleet types into 3 types for estimating the overall impacts of IM program intervention on the decision behaviors of vehicle owners. Next, the formal operationalization of linking empirical data to theoretical questions is presented, but again, the results need to be interpreted in the light of limitations listed above.

The percentage of cooperative vehicle owners in the sample is measured by taking a ratio of the vehicles in the cooperative fleets to the vehicles in all of the treatment groups. Formally, as also shown in equation 1.6:

(5.1): % (cooperative types) = $100*[Q_6 + Q_7]/[\ Q_6 + Q_7 + Q_8 + Q_9 + Q_{10} + Q_{11}]$

Conversely, the percentage of non-cooperative vehicle owners in the sample is measured by taking a ratio of the vehicles in the non-cooperative fleets to the vehicles in all of the treatment groups. Formally:

(5.2): % (non-cooperative types) = $100*[Q_6 + Q_7 + Q_8 + Q_9]/[\ Q_6 + Q_7 + Q_8 + Q_9 + Q_{10} + Q_{11}]$

5.5.2 The impact on vehicular tail-pipe emissions due to vehicle owners' decision behaviors

Phase II of this research design empirically explores the following question: What is the impact on the vehicular emissions due to the cooperative and non-cooperative decision behaviors of high-emitters in the Atlanta airshed, while controlling for other important parameters that affect the vehicular tail-pipe emissions? Multiple statistical decision theory models, employing multivariate generalized linear and non-linear regressions are used to test hypotheses concerning the impacts of cooperative and non-cooperative strategies of high-emitters on on-road vehicular emissions. More importantly, changes in the impacts are measured over time between 1997 and 2001, for which purpose the classical quasi-experimental methodology of mixed pooling of data is employed.

5.5.2.1 Mixed-pooled generalized linear regression models

First, mixed-pooled generalized linear (GL) regression models are used to study the effect of cooperative and non-cooperative behavioral strategies of high-emitters on CO, HC, and NOx, exhaust emissions over time. Mixed-pooled generalized linear models have following initial mathematical form, as also shown in equations 1.7-1.9:

5.3: $Y_{CO} = \alpha_0 + \sum_{q=2}^{11} \beta_q Q_q + \sum_{r=1}^{29} \gamma_r R_r + \sum_{s=1}^{7} \phi_s S_s + \sum_{t=2}^{5} \delta_t T_t + \sum_{t=2}^{5}\sum_{q=2}^{11} \Delta_{tq} T_t Q_q + \varepsilon_1,$

5.4: $Y_{HC} = \alpha_0 + \sum_{q=2}^{11} \beta_q Q_q + \sum_{r=1}^{29} \gamma_r R_r + \sum_{s=1}^{7} \phi_s S_s + \sum_{t=2}^{5} \delta_t T_t + \sum_{t=2}^{5}\sum_{q=2}^{11} \Delta_{tq} T_t Q_q + \varepsilon_1,$

5.5: $Y_{NO} = \alpha_0 + \sum_{q=2}^{11} \beta_q Q_q + \sum_{r=1}^{29} \gamma_r R_r + \sum_{s=1}^{7} \phi_s S_s + \sum_{t=2}^{5} \delta_t T_t + \sum_{t=2}^{5}\sum_{q=2}^{11} \Delta_{tq} T_t Q_q + \varepsilon_1,$

Where Y variables show CO, HC and NO emission factors in grams per gallon, Q variables show 10 fleet types grouped by decision behavior. The control fleet is the reference group. R variables show vehicular characteristics including their emission control technological systems. A Ford car made in USA of zero years of age is the reference group.[91] S variables show the physical and atmospheric contextual conditions at the time of remote sensing measurements and T variables show the observation year. 1997 is the base year. The interaction terms (T x Q) track over time the changes in the emission factors of the 11 fleet types during the study period. Column 2 in table 5.1 shows the relevant symbol for each individual variable shown in equations 5.3 to 5.5.

Section 5.6.3 elaborates in detail the classical assumptions associated with the generalized linear models and presents the detection and correction methods that are employed to correct the violations of these classical assumptions. Since evidence for heteroskedasticity is found in the data, as well as non-linearities in vehicular emissions are observed in sample statistics, first an attempt is made to correctly specify the functional form of the models -- such as through Box-Cox regressions.

In order to estimate the non-linearities in the functional form between the dependent and the independent variables, best non-linear fits for the dependent variables are estimated. More specifically, following Box-Cox (1964) transformation parameters (λ) are estimated by using the maximum likelihood estimation techniques:[92]

(5.6): $Y_{CO}^{(\lambda)} = \alpha_0 + \sum_{q=2}^{11} \beta_q Q_q + \sum_{r=1}^{29} \gamma_r R_r + \sum_{s=1}^{7} \phi_s S_s + \sum_{t=2}^{5} \delta_t T_t + \sum_{t=2}^{5}\sum_{q=2}^{11} \Delta_{tq} T_t Q_q + \varepsilon_1,$

(5.7): $Y_{HC}^{(\lambda)} = \alpha_0 + \sum_{q=2}^{11} \beta_q Q_q + \sum_{r=1}^{29} \gamma_r R_r + \sum_{s=1}^{7} \phi_s S_s + \sum_{t=2}^{5} \delta_t T_t + \sum_{t=2}^{5}\sum_{q=2}^{11} \Delta_{tq} T_t Q_q + \varepsilon_1,$

---

[91] In addition, variables age-square and age-cube are added to capture the non-linear trends in vehicular tail-pipe emissions as a function of vehicle age.

[92] It is possible to estimate λ for independent parameters too, but that would require all independent parameters to have positive values. Due to computational complexity, this task is left for the future research.

(5.8): $Y_{NO}{}^{(\lambda)} = \alpha_0 + \sum_{q=2}{}^{11} \beta_q Q_q + \sum_{r=1}{}^{29} \gamma_r R_r + \sum_{s=1}{}^{7} \phi_s S_s + \sum_{t=4}{}^{5} \delta_t T_t + \sum_{t=4}{}^{5} \sum_{q=2}{}^{11} \Delta_{tq} T_t Q_q + \varepsilon_1,$

Where $\varepsilon_i \sim N(0, \sigma^2)$ and the dependent variables Y_P [for P = CO, HC and NO] are subject to a Box-Cox transform[93] with parameter λ. The significance and direction of independent parameter values on Box-Cox transformed dependent variables are tested through likelihood ratio tests. More importantly, the estimated value of the parameter λ guides the researcher to approximately estimate the non-linearities through transformed values of dependent variables in the linear GLM models. Specifically, as extensively discussed by Davidson and MacKinnon (1993), a linear form of dependent variable is retained if λ is (approximately) equal to 1, a logarithmic transformation of the dependent variable is carried out if λ is (approximately) equal to 0, and an inverse multiplicative transformation of the dependent variable is carried out if λ is (approximately) equal to -1. Formally:

(5.9): $y^{(\lambda)} = \{y-1 \text{ if } \lambda =1, \ln(y) \text{ if } \lambda=0, \text{ and } (1-1/y) \text{ if } \lambda=-1\}$

As inferred from the Box-cox regression results shown in tables 6.2-6.4, the log-linear models are run for equations 5.3 to 5.5 by transforming the dependent variable into its natural logarithm equivalents. Secondly, heteroskedasticity is corrected by employing multiple methodologies. First, heteroskesdasticity is corrected by using White's (1980) robust variance estimator methods. Second, weighted least squares (WLS) regression model is used to generate more efficient standard errors and correct for heteroskedasticity. Third, robust regression techniques (Berk 1990) are employed to counter-test the significance and direction of the independent parameters, as estimated in White's robust and WLS methods.

Figure 5.10 shows the 6 graphs of the residuals versus the fitted values: 3 each for OLS with a robust errors model and the other 3 each for log-linear with robust errors models, which were employed, among other models, to estimate equations 5.3 to 5.5. The graphs showing OLS models clearly indicate that the assumption of homoskedasticity is violated in all the three equations estimated by OLS model, especially the equation for HC seems specially affected by heteroskedasticity (which explains relatively low R^2 values [8.52%] for OLS models predicting HC emission factors). The graphs showing log-linear model, however, present a much-improved

---

[93] A Box-Cox transform function is defined as follows: $Y^\lambda = [Y^\lambda - 1]/\lambda$.
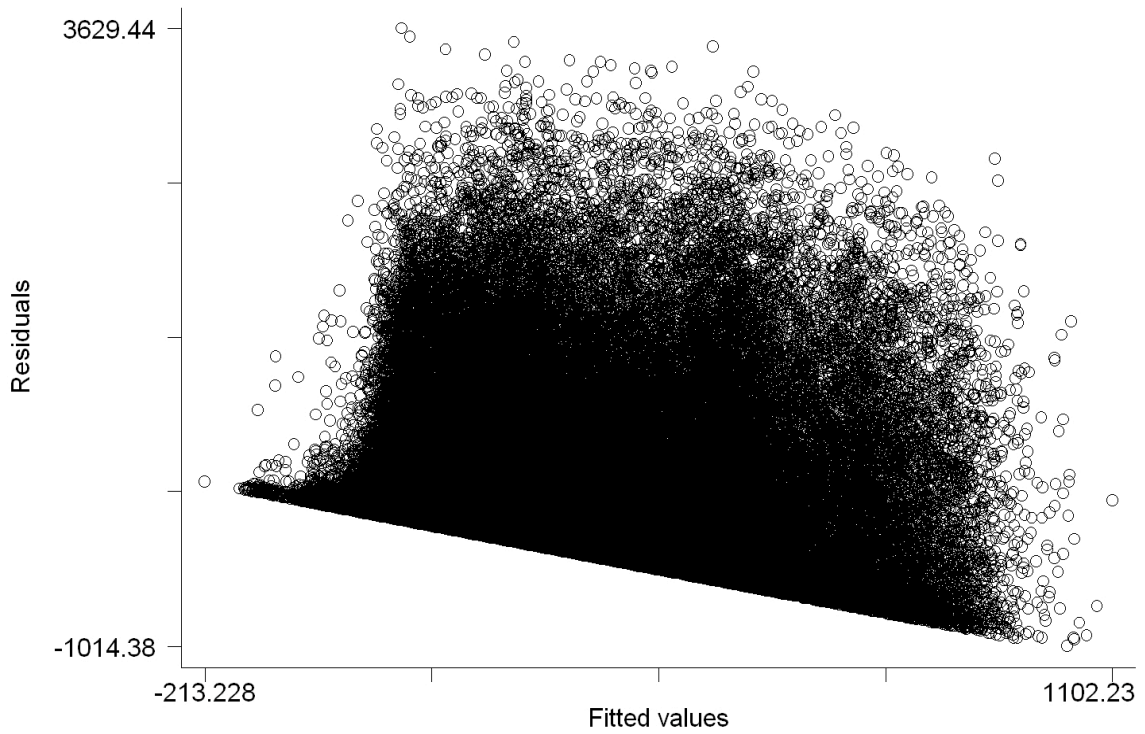
Panel (a): OLS model predicting CO emission factors (equation 5.3)
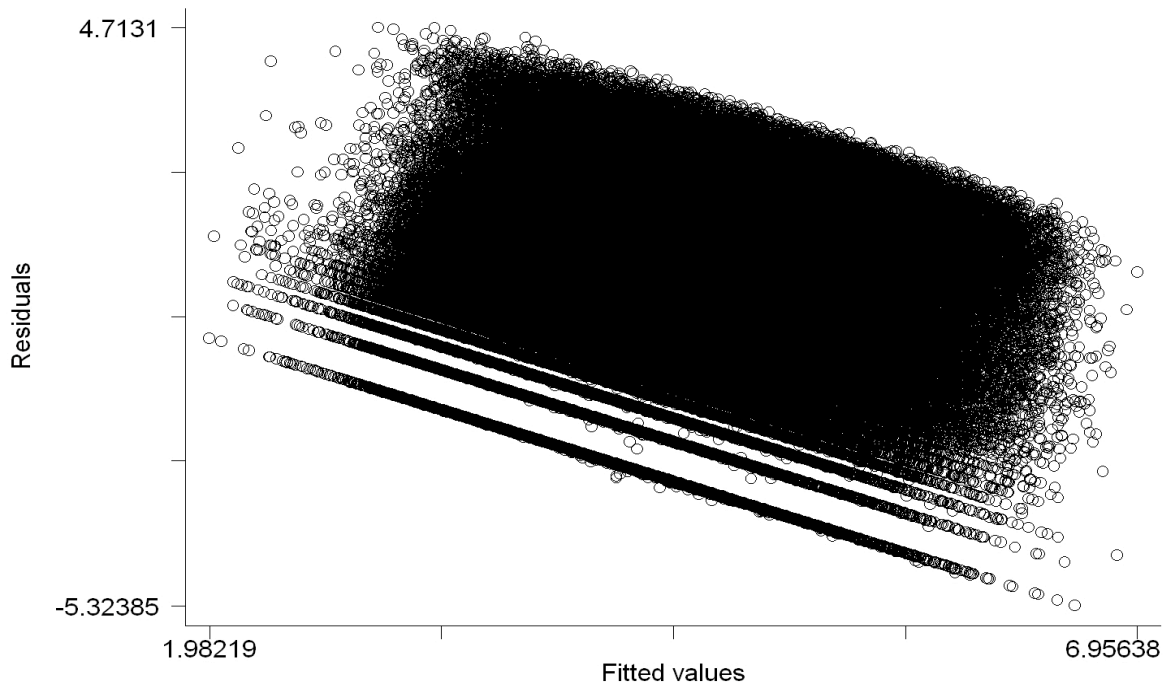
Panel (b): Log-linear model predicting CO emission factors (equation 5.3)
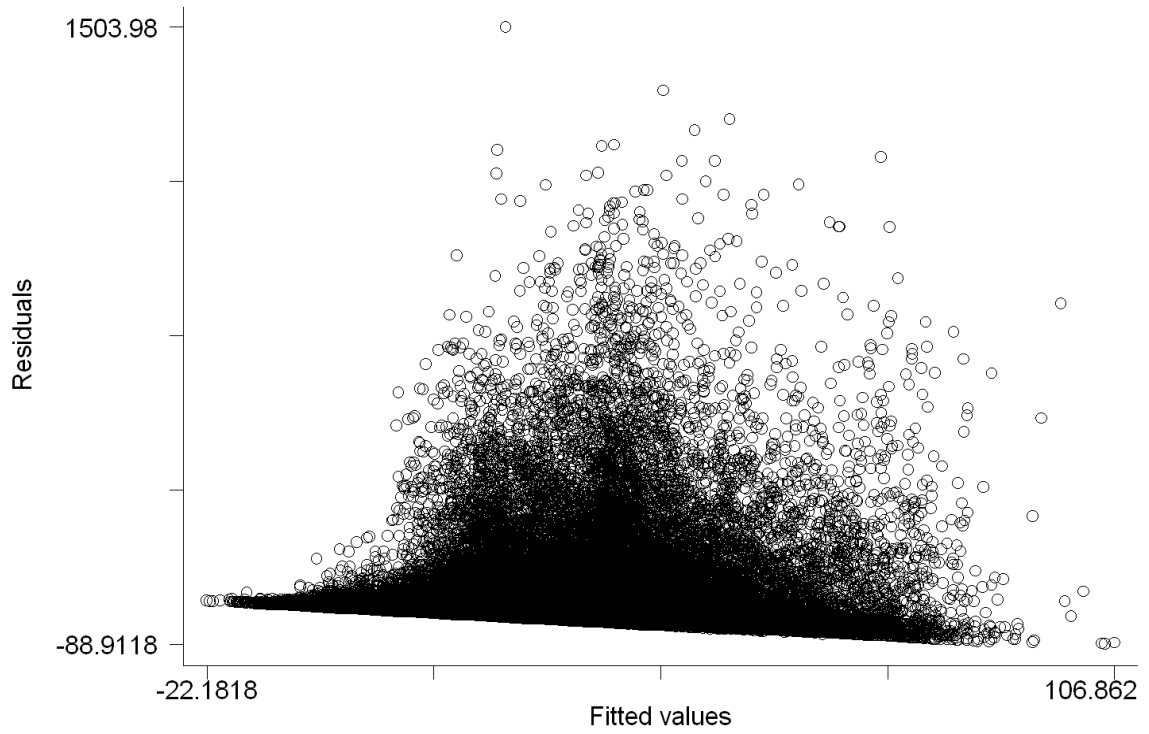
Panel (c): OLS model predicting HC emission factors (equation 5.4)
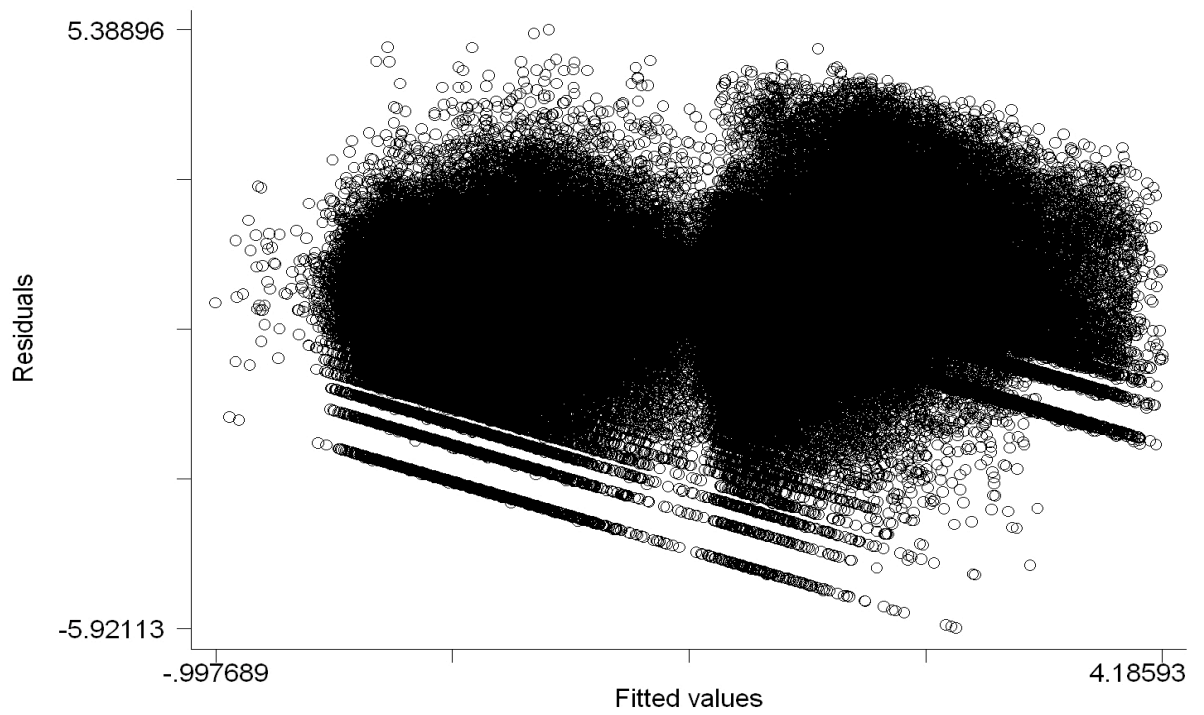
Panel (d): Log-linear model predicting HC emission factors (equation 5.4)
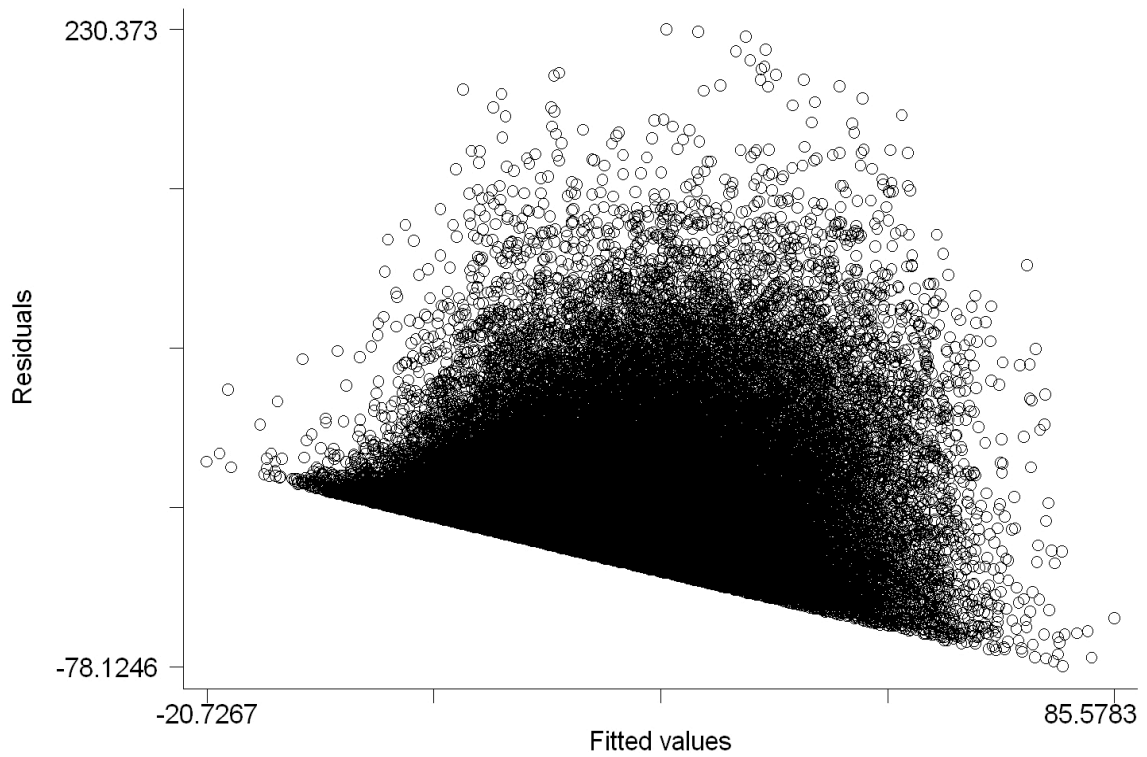
Panel (e): OLS model predicting NO emission factors (equation 5.5)
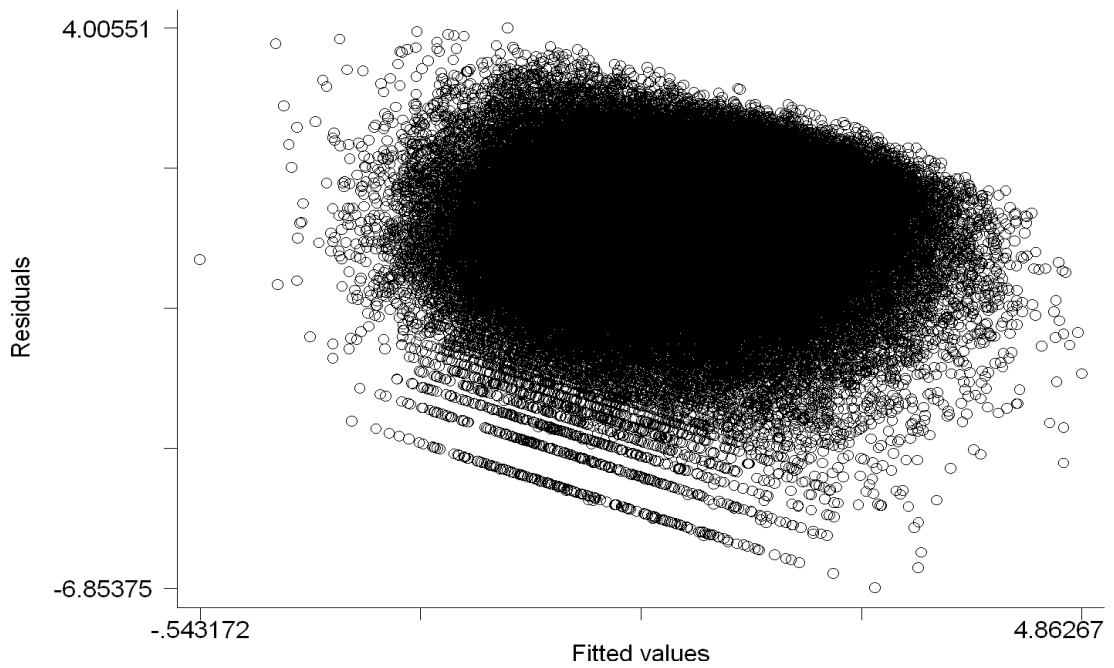
Panel (f): Log-linear model predicting NO emission factors (equation 5.5)

Figure 5.10: Graphs of the residuals versus the fitted values for OLS and log-linear models predicting CO (panels a and b), HC (panels c and d) and NO (panels e and f)

picture and the errors appear to be distributed around its mean more evenly as compared to the OLS models. The log-linear model for HC especially showed vast improvement in terms of its explanatory power, the adjusted R^2 being 49.31%. However, the log-linear models with robust errors still show non-constant error variance, for which reason the results from WLS models are estimated.

Results from the robust regression models are also reported in chapter 6 and are used to counter-validate the inferences drawn from log-linear with robust errors and WLS models. In addition, the Chow test is undertaken by adding interaction terms of time variables $[T_t]$ with the decision variables $[Q_q]$ in equations 5.1-5.3. The Chow test permits the testing of hypotheses whether or not the impact of decision behaviors on vehicular exhaust emissions is structurally consistent across time, provided all the other independent parameters are held constant.

5.5.3 The contextual conditions of cooperative and non-cooperative decision makers

The contextual conditions of decision makers (i.e. vehicle owners in 11 fleet types) are ascertained through two kinds of models: First, linear ecological regression is employed to test the differences in the median household income of vehicle owners' block-groups as per 11 fleet types. In order to finely test the spatial distribution of median household income for 11 fleet types, while controlling for other vehicular parameters as well as social, demographic and economic variables, the following ecological regression equation is estimated:

$$(5.10): W_1 = \alpha_0 + \sum_{q=1}^{10} \beta_q Q_q + \sum_{r=1}^{29} \gamma_r R_r + \sum_{w=2}^{14} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t + \varepsilon_1$$

Secondly, a multinomial variable "fleet type" [F] is created, which is coded 0 for control group, 1 for the IM ineligible group, 2 for the waived fleet, 3 for the rest of Georgia fleet, 4 for the missing fleet, 5 for the retest pass fleet, 6 for the migrated pass fleet, 7 for the retest fail fleet, 8 for the migrated fail fleet, 9 for the missing fail and 10 for the missing pass fleet. In order to test the hypotheses about the social, economic and demographic contextual conditions of different groups of decision-makers/vehicle owners that affect the probability that a vehicle owner will be in one of the 10 groups relative to the control group, the following multinomial logistic regression equation 5.11 is estimated. The control group is the base category, while white male drivers of US-manufactured Ford vehicles under the ages of 18 years are treated as the reference group in equation 5.11.

(5.11.1): $\Pr(\text{In-eligible})/\Pr(\text{control}) = e ** [\sum_{r=1}^{29} \gamma_r R_r + \sum_{w=1}^{15} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t]^{\text{ineligible}}$

(5.11.2): $\Pr(\text{waived})/\Pr(\text{control}) = e ** [\sum_{r=1}^{29} \gamma_r R_r + \sum_{w=1}^{15} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t]^{\text{waived}}$

(5.11.3): $\Pr(\text{rest-of-GA})/\Pr(\text{control}) = e ** [\sum_{r=1}^{29} \gamma_r R_r + \sum_{w=1}^{15} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t]^{\text{rest-of-GA}}$

(5.11.4): $\Pr(\text{missing})/\Pr(\text{control}) = e ** [\sum_{r=1}^{29} \gamma_r R_r + \sum_{w=1}^{15} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t]^{\text{missing}}$

(5.11.5): $\Pr(\text{retest-pass})/\Pr(\text{control}) = e ** [\sum_{r=1}^{29} \gamma_r R_r + \sum_{w=1}^{15} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t]^{\text{retest-pass}}$

(5.11.6): $\Pr(\text{mig-pass})/\Pr(\text{control}) = e ** [\sum_{r=1}^{29} \gamma_r R_r + \sum_{w=1}^{15} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t]^{\text{mig-pass}}$

(5.11.7): $\Pr(\text{retest-fail})/\Pr(\text{control}) = e ** [\sum_{r=1}^{29} \gamma_r R_r + \sum_{w=1}^{15} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t]^{\text{retest-fail}}$

(5.11.8): $\Pr(\text{mig-fail})/\Pr(\text{control}) = e ** [\sum_{r=1}^{29} \gamma_r R_r + \sum_{w=1}^{15} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t]^{\text{mig-fail}}$

(5.11.9): $\Pr(\text{miss-fail})/\Pr(\text{control}) = e ** [\sum_{r=1}^{29} \gamma_r R_r + \sum_{w=1}^{15} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t]^{\text{miss-fail}}$

(5.11.10): $\Pr(\text{miss-pass})/\Pr(\text{control}) = e ** [\sum_{r=1}^{29} \gamma_r R_r + \sum_{w=1}^{15} \kappa_w W_w + \sum_{t=1}^{4} \delta_t T_t]^{\text{miss-pass}}$

5.6 Threats to validity and limitations of the research design

This section discusses the major limitations and key assumptions of the proposed quasi-experimental research design. Cook and Campbell (1979) is considered a standard text for designing quasi-experiments, and they consider it useful to evaluate the impact of the limitations and key assumptions of a study based on potential threats to four types of validity (Cook and Campbell 1979:chapter 2). This section discusses the limitations and key assumptions of this study in the light of their potential threat to the internal, statistical, construct and external validities of this quasi-experimental research design.

5.6.1 Threats to internal validity and corresponding limitations

Since this research design utilizes remotely sensed on-road vehicle emissions data to quantify the impact of cooperative and non-cooperative behavioral strategies of vehicle owners on on-road vehicular emissions, it relies on the quality of measurements made by the remote sensing instruments of the AQL. A key threat to the internal validity of this study is the potential for measurement error due to the use of multiple instruments in collecting the on-road data. The WLS regression models show that the instrumentation effect is significant. The results of this study should be interpreted in the light of this major limitation.

Another difficulty in using remote sensing data is the problem of negative values for CO, NOx and HC measurements on emission concentrations, which, theoretically, are not possible. The negative values are generated during the estimation process of CO, NOx and HC by a remote sensing device when combustion equations employ

regression methods and the error values are larger than the absolute measurements of these pollutant concentrations. These negative values pose a serious problem for converting emission concentrations into emissions factors (expressed as grams per gallon, as explained in appendix A). Further, for the purposes of estimating non-linear models such as Box-Cox transforms (as explained in section 5.6.2), it is absolutely necessary that the dependent variable be strictly positive. There is no best solution to resolve the problem of negative values for CO, HC and NOx in this case. One way to resolve this problem will be to treat all the negative values as equal to zero. This will, however, bias the coefficients of the regression models, which is not desirable. Another possibility is to add all the measurements with a constant for making them greater than zero, which will also bias the coefficients in non-linear models. In order to avoid these biases, as well as measuring the parametric effects on vehicular tail-pipe emissions in more meaningful units of grams per gallon, observations that have negative values on CO, HC and NOx emissions concentrations were dropped from the sample. Did this bias the sample? One could argue "no", because, first, negative values of emissions are not possible in theory, especially as per the second law of thermodynamics; second, if observations based on other validity criteria, such as non-matching in Georgia's vehicle registration database, can be dropped to get meaningful information about the parameters of the models, it doesn't make much difference to consider negative values on CO, HC and NOx as invalid observations; third, the sample size, even after dropping the observations with negative values from the sample remains sufficiently large, as shown in CO, HC and NOx descriptive statistics in table 5.1, which are measured in grams per gallon. Despite these theoretical caveats that justify removal of negative valued observations, empirical scrutiny shows that the mixed sample is biased because vehicles with higher mean age are more likely to be included in the sample without the negative values.[94]

The key threat to internal validity of this research design is the issue of sample selection, as described in previous paragraph, as well as due to the following reasons.

---

[94] Of the 777,408 observations in the mixed pool sample (1997-2001), CO %, HC PPM and NO PPM respectively had strictly positive values on 673,728 (86.7%), 511,611 (65.8%) and 119,528 (15.4%) observations; negative or zero values on 101,878 (13.1%), 230,208 (29.6%) and 16,958 (2.2%) observations; and missing values on 1802 (0.2%), 35,539 (4.6%) and 640,922 (82.4%) observations. The null hypothesis that the vehicle age is same for the sample with and without the negative values is rejected by a t-test for all the three pollutants. Vehicle age is higher for the sample without the negative values.

The remote sensing data has over 1.42 million observations between 1997 and 2001, and the AQL data collection team has made conscious efforts to select a broad variety of sites for making the data broadly representative of the Atlanta fleet. Still it is possible that the site selection could bias the results of this study. Second, license plates were not readable for 20% of the 1.42 million vehicles in the raw sample that biases the results. Third, 21.2% of the 1.13 million readable license-plate sample was dropped because it was not found in the Georgia registration database, which biases the results. Fourth, removal of observations with negative values, as discussed in the previous paragraph, biases the sample. Fifth, while estimating emission factors in grams per gallon, 30.7% of positive CO and 8.8% of the positive HC observations are dropped because CO and HC is not measured for a vehicle at the same time. A two-sample t-test shows that this biases the sample as vehicles with observations on both CO and HC are slightly higher in their age as compared to the vehicles with non-conjoint observations on CO and HC.

The remote sensing sample captures vehicles from all the 13 counties during the five years of the study period. Yet there remain differences in geographical and age distributions of on-road and registered vehicle fleets. The sample selection thus poses an important limitation to the internal validity of this research design.

5.6.2 Threats to statistical validity and corresponding limitations

The generalized linear models presented in equations 5.3-5.5 are based on six major assumptions (Greene 2000):

1. $\mathbf{Y} = \mathbf{X}\beta + \varepsilon$, where $\mathbf{X}$ is a MxK matrix of Q + R + S + T + Q*T variables, M shows the number of observations and K = 1, 2, ...90 shows the number of parameters.
2. $\mathbf{X}$ is a M x K matrix with rank K
3. $E\,[\varepsilon/\mathbf{X}] = 0$
4. $E\,[\varepsilon\varepsilon'/\mathbf{X}] = \sigma^2 I_T$
5. $\mathbf{X}$ is a known M x K matrix of constants
6. $\varepsilon/\mathbf{X} \sim N\,[\,0,\,\sigma^2 I_T]$

Assumption 1 is violated if $\mathbf{X}$ is a non-linear function of $\mathbf{Y}$ or it is not correctly specified. As explained in section 5.5.2, the non-linear functional form is tested through Box-Cox regression models. Furthermore, the assumption of a correctly specified model is tested for omitted variable bias by using the Ramsey (1969) test. This test estimates

the regression $Y_i = \mathbf{X}b + \mathbf{Z_i}t + u_i$, where either $Z_i = (Y_i\text{-hat}^2, Y_i\text{-hat}^3, Y_i\text{-hat}^4)$ or $Z_i = (x_{1i}^2,$ $x_{1i}^3, x_{1i}^4, x_{2i}^2, x_{2i}^3, \ldots, x_{mi}^4)$ and it performs a standard F test for $t = 0$. The LINK test is also used to test the omitted variable bias. Both Ramsey and LINK tests show that there is omitted variable bias in the five regression models of equations 5.3 and 5.4, but there is no omitted variable bias in estimators of equation 5.5. Vehicle mileage, vehicle make and model are some of the important variables omitted from these regression models. The odometer data for measuring the vehicle mileage is not reliable, while the variables on vehicle make and model are consciously omitted to keep the regression models computable.

The second assumption that $\mathbf{X}$ is a M x K matrix with rank K is also known as an assumption of non-multicollinearity among the independent variables. This assumption is tested by estimating the Variance Inflation Factors (VIF) for each of the independent variables in $\mathbf{X}$ by using the following formula provided by Chatterjee et al. (2000): VIF (x_j) $= 1 / (1 - R_j^2)$, where R_j^2 is the square of the multiple correlation coefficient that results when x_j is regressed against all the other explanatory variables. If VIF of an independent variable appears to be exceeding the value of 30 (Chatterjee et al. 2000: 242-4), then that variable is considered to be multi-collinear with other covariates, and possibly can be removed from the equation. No variable in equations 5.3 to 5.5 was found to be multi-collinear (i.e. VIF > 30), except age-square and age-cube that are included to model the non-linear effects of vehicle age on vehicular tail-pipe emissions.

If the third assumption that $E[\varepsilon/\mathbf{X}] = 0$ is violated then the intercept of the regression equation will be biased, but the regression coefficients will remain unbiased (Green 2000). Violation of the fourth assumption that $E[\varepsilon\varepsilon'/\mathbf{X}] = \sigma^2 I_T$ can be tested by using the Durbin-Watson d statistic, which is measured as follows:

$$d = [\textstyle\sum_{j=1}^{n-1} (e\text{-hat}_{i+1} - e\text{-hat}_i)^2]/ [\textstyle\sum_{j=1}^{n} e\text{-hat}_i)^2$$

If the value of d statistic is significantly below 2, then there will be evidence of positive autocorrelation. In theory, mixed pool designs do not normally have the problem of autocorrelation. However, the park test shows that the log of the squared residuals is significantly explained by the temporal parameters in estimating equations 5.3-5.5, which suggests that errors are correlated across time.

The fifth assumption that $\mathbf{X}$ is a known M x K matrix of constants concerns the fact that there is no measurement error in the model and that the measurement values of

the independent variables are fixed. This assumption limits the inference power of regression results from the samples to the population parameters.

The sixth assumption that $\varepsilon/\mathbf{X} \sim N\ [\ 0,\ \sigma^2 I_T]$ is violated if there is evidence of heteroskedasticity in the error terms. Figure 5.10 shows an eyeball test for heteroskedasticity. Formally, this assumption is tested using Cook-Weisberg (1983) test for heteroskedasticity. This test models Var $(e_i) = \sigma^2 \exp(\mathbf{z}t)$ where $\mathbf{z}$ is either a variable suspected to be causing heteroskedasticity or equal to the fitted values $\mathbf{Xb}$. The test is of $\mathbf{t} = 0$. This test estimates the model (e-hat$_i^2$) = a + z$_i\mathbf{t}$ + v$_i$ and then forms the score test S equal to the model sum of squares divided by 2. Under the null hypothesis, S has the χ^2 distribution with m degrees of freedom, where m is the number of columns of $\mathbf{z}$.   Since the assumption of homoskesdaticity is violated in the measured models, as explained in section 5.5.2, models with White's robust errors are estimated and Berk's robust and WLS regressions are used to counter-validate the White's robust models. The log-linear models appear to drastically reduce heteroskesdicity, but the Cook-Weisberg test still shows heteroskesdacity. The results from WLS regression models are thus most valid.

5.6.3 Threats to construct validity and corresponding limitations

The decision variables, such as those representing groups/fleets of vehicles as per decision behaviors of drivers in response to IM intervention, are constructed to test the central research hypotheses. These constructs are used to (1) compare cooperative with non-cooperative decision behaviors, (2) evaluate the impact on vehicular tail-pipe emissions due to the decision behaviors, and (3) determine the socio-economic contextual condition of cooperative and non-cooperative decision makers.

While it is not possible to observe each individual's strategy through a ubiquitous camera, these variables are constructed within the confines of the new information made available by remote sensing data. The validity of these constructs comes from the fact that the vehicles observed on-road are tracked in the IM program data and then a decision is made on the basis of the track record of that vehicle owner in the IM program data whether s/he appears to be in the control or treatment (cooperative or non-cooperative) fleet, as extensively discussed in section 1.3. The limitations in the empirical observation of these constructs are discussed in section 5.5.1.

The validity issues related to the remotely sensed measured constructs pose a serious limitation to the results of this study because remote sensors only measure in a

split second the emission levels of a car in a pre-selected site. Furthermore, the pollutants are not measured in absolute terms, rather they are measured as ratios and are derived from the knowledge-base of atmospheric chemistry, physics and other earth and natural sciences. The CO, HC and NOx constructs transformed into mass emission factors (in grams/gallon) and mass emission rates (in tons per year) represent meaningful policy and scientific concepts well-represented in the discourse in the research area of this dissertation, which is why they are used.

Another potential issue of construct validity in this research concerns the use of census block-group level socio-economic and demographic variables, such as median household income and the set of variables symbolized as W in section 5.5.3. The validity of socio-economic constructs [W variables] can be far greater if they were measured at household or individual level. Such measurement is unfortunately not possible at this time due to both financial resource constraints as well as privacy rights issues of the research subjects. The ecological fallacy issue with respect to the multiple-level contextual analysis is discussed in some detail in section 1.4.

The interpretation of results associated with coefficients of W constructs is cautiously undertaken by explicitly stating that these constructs do not represent the vehicle owner; rather they represent the census block-group of vehicle-owner's address. If vehicle-owners were registered with false addresses, the validity of these constructs would be further doubtful, further limiting the results of this study.

5.6.4 Threats to external validity and corresponding limitations

Due to the correlation of on-road vehicle emissions with a host of confounding and un-observed effects, such as weather variability at the specific sites of emission measurements, large variability in individual driving behaviors/patterns, different vehicle-maintenance behaviors, and transportation infrastructure quality, it is not easy to generalize the *conclusions* of this study beyond the Atlanta airshed. However, the results of this study are comparable to the similar studies in other ozone non-attainment urban airsheds, because the generalized linear and non-linear models of this research are using a large set of control parameters [as shown in equations 5.3-5.5]. It is thus possible to compare the results of this study with other relevant studies, which also employ similar control parameters.

This research will externally validate the recent results obtained by Pokharel et al. (2000), which suggest that the variables "speed", "acceleration" and the "road grade"

can be used to systematically estimate a variable called "vehicle specific power", which in turn can be used as a proxy variable to estimate the impact of on-road vehicle-load conditions on the vehicular emissions. Similarly the results estimating the lack of IM program effectiveness in reducing the vehicular emissions due to drivers' decision behaviors is of considerable interest to the research community. For example, a recent National Research Council (2001) study recommended more independent evaluation studies of drivers' decision behaviors due to the IM programs as a guide to policy makers.

CHAPTER 6

THE RESEARCH RESULTS

6.1: Introduction

Chapter 6 presents a discussion of some important results of the empirical research design that was elaborated in previous chapters, especially chapter 5. First, the estimated probability of cooperative and non-cooperative decision behaviors of high-emitting vehicle owners in the Atlanta airshed is discussed in the next section. The empirical results are employed to test H_1 that was posed in section 1.3.

Second, section 6.3 presents, in relatively greater detail, the results of the investigation that aims at measuring the impact of vehicle owners' actions/decisions on the environmental outcomes, which are CO, HC and NO tail-pipe vehicular emissions in this case. Since this is a complex undertaking and involves interpretation of estimated equations (5.3-5.5) with up to 90 parameters, I focus on analyzing the *ceteris paribus* impact of human decision behaviors on environmental outcomes.

More specifically, sections 6.3.1 to 6.3.3 present respectively the impact of human decision behaviors on CO, HC and NO emission-factors. In the process, the results of H_2 are also presented. For the sake of brevity, the remaining details about the controlling parameters can be seen in the tables of chapter 6 that summarize the results of empirical models. Section 6.3.4 presents the impacts of vehicle owners' actions on vehicular emissions that are measured as mass emission rates, which are estimated through the methods presented in appendix A.

Section 6.4 presents the results from the third and final phase of the empirical study. First, in section 6.4.1, the socio-economic and demographic contextual conditions of the cooperative and non-cooperative decision makers are compared with each other and the other control groups in the study. Second, in section 6.4.2, the outcomes of an environmental policy intervention, which is the IM program in this case, are measured on the value of fairness. The results of H_3 are also discussed in this section. Furthermore, it is also discussed in section 6.4.2 whether cooperative and non-cooperative vehicle

owners, *ceteris paribus*, come from similar income level neighborhoods. In this context, the results of H_4 are also presented in this section. Chapter 7 discusses the implications of these results.

6.2: Probability of cooperative and non-cooperative decisions

Table 6.1 presents the probability of cooperation in each of the five years of study, as estimated by measuring equation 5.3. These results should be strictly interpreted in the light of limitations extensively discussed in section 5.5.1. Overall, 41.22% of the vehicle owners in the total treatment sample appear to be cooperative, and conversely 58.78% non-cooperative. Except for the base year of 1997, the probability of cooperation is between 36% and 41% during the period 1998 to 2001.[95] H_1, that the probability of cooperation is zero is rejected, which means that the prediction of classical game and/or rational choice theory does not hold. It is also noticeable that the probability of cooperation is not 100%, which means that the prediction of those sociology and political science theories that suggest all people put their group level interest above their selfish interest also does not hold.

Table 6.1: Probability of Cooperation = $[Q_6 + Q_7]/[Q_6 + Q_7 + Q_8 + Q_9 + Q_{10} + Q_{11}]$

Probability (Cooperation)	1997	1998	1999	2000	2001	Total
Full sample (N=777,408)	83.75%	37.86%	39.28%	41.00%	36.64%	41.22% (N=51,894)
Geocoded sample (N = 519,416)	84.74%	35.98%	38.11%	41.20%	37.96%	40.68% (N=36,419)
Sample with CO and HC measured in Grams/Gallon (N = 466,640)	82.02%	39.74%	40.84%	41.77%	38.12%	42.17% (N=36,433)

Probability of non-cooperation = [1 – probability of cooperation]

Most strikingly, the results confirm the findings of earlier controlled lab experimental studies (as reviewed in chapter 2, especially section 2.3.1), which also found the probability of cooperation between 40% and 60% of the group optimum under voluntary mechanisms. The surprising aspect of these results thus resides in the

[95] The 1997 result, which shows probability of cooperation at 83.75%, is an outlier in the temporal trend because no vehicles in the 1997 remote sensing sample were found in four treatment groups: migrated pass, migrated fail, missing fail, missing pass. 1997 is an exception because it was the first year of the "enhanced" IM program and no vehicles in these four categories were matched with "basic" IM program data that was collected in Atlanta in 1995 and 1996.

similarity of human decision behavior under the contexts of voluntary and regulatory mechanisms, on the one hand; and laboratory and real-world situations, on the other hand.

Ledyard's (1995) prediction – that there are 50% Nash players, 40% respond to incentives while the behavior of the remaining 10% is inexplicable – also appears to be partially supported by the results. In this case, 59% to 63.36% of the annualized samples appear to be non-cooperative, which is a little higher than Ledyard's prediction of 50%.

But how would game theory/RCT explain the observed 40% cooperative players under IM program's regulatory mechanism? Presumably, it would be said that these players did not have complete information about all the alternative courses of actions available to them and that they are responding to the incentive structure of regulatory punishment on its *face value* set up under IM program and thus appear to be cooperative. On the other hand, it can be argued from the perspective of political science theory, which takes players as good citizens, that cooperative players are also rational but in a different sense than presumed by game theory. These players know about the alternative/non-cooperative courses of action but they consciously choose to be cooperative because it promotes the greater good of the society of which they are a part. The debate between alternative theories about human decision behavior could thus be continued indefinitely. As argued before, it is extremely important to see these cooperative and non-cooperative decision behaviors under their specific contexts. Before presenting the individual and group-level socio-economic and demographic contexts of cooperative and non-cooperative decision-makers in section 6.4, the impacts of cooperative and non-cooperative decision behaviors of vehicle owners on vehicular emissions are presented in section 6.3.

6.3: The impact of cooperative and non-cooperative decisions on vehicular tail-pipe emissions

The impact of cooperative and non-cooperative decisions on vehicular emissions in the Atlanta airshed between 1997 and 2001 is estimated by the empirical measurement of equations 5.3-5.5. Tables 6.2 to 6.4 present the estimated empirical parameters for equations 5.3 to 5.5 respectively. Table 6.2 shows the predicted parameters of the OLS with the robust errors model, Box-Cox regression model, the log-linear with robust errors model, the log-linear weighted least squares (WLS) model and

150

the log-linear robust regression model when all the independent variables, as shown in equation 5.3, are regressed against CO (grams/gallon) observed in the mixed pool remote sensing data. Similarly, Table 6.3 shows results of 5 regression models for the mixed pool remote sensing samples, when HC is regressed against all the independent variables. Finally, Table 6.4 shows results of 5 regression models for mixed pooled remote sensing samples between 1999 and 2001 when NO is regressed against all the independent variables.

Each table 6.2-6.4 shows adjusted R^2 and root MSE statistics for each model except Box-Cox and robust regression models because they present log-likelihood estimators. F/LR-test statistic for each of the five models in the three tables is also reported. The null-hypothesis for the F/LR-test states: all the independent variables in the estimated model do not jointly explain in a significant manner the variation in the dependent variable. F/LR test statistic in tables 6.2 to 6.4 shows that the null hypothesis is rejected in all the 15 models presented in these three tables, which means that these models are not irrelevant. The parameter "lambda", as shown in tables 6.2 to 6.4, reports a Box-Cox transform estimator, which is empirically estimated for Box-Cox non-linear regression models but assumed exogenously constant for the other four models. Finally, each coefficient value is reported against the independent variables for each of the five regression models in all the three tables 6.2 to 6.4. Under the coefficient values, numbers in brackets show the estimated standard errors of those coefficient values; while stars above the coefficients values indicate the statistical significance of those variables.

There was no evidence of multi-collinearity found in the OLS models. All the OLS models however showed evidence for heteroskedasticity as the Cook-Weisburg test for each OLS model rejected the null hypothesis of no heteroskedasticity. The inferences from the OLS models are therefore not very reliable. Since the Box-Cox regression model for each CO, HC and NO predicted a lambda value near 0, the log-linear models present more valid results as compared to the OLS with robust errors model. Further, the results from WLS and Robust regression models are used to cross-check the inferences drawn in the log-linear with robust-standard errors model. Thus, the significance, direction and size of the effect of each parameter is comparable across these five models for each pollutant CO, HC and NO.

Parameters in the OLS with robust errors model present the change in absolute CO, HC and NO emission factors (in grams per gallon) as unit change in the independent parameter is introduced, while log-linear, WLS and robust regression models present % change in emission factors.[96] Since Lambda values in Box-Cox regression models are close to zero, they can also be interpreted in terms of percentage change.[97]

Next, the predicted impacts of cooperative and non-cooperative behavioral strategies of high-emitters on CO, HC and NOx emissions, while controlling for other independent parameters, are presented.

6.3.1: Impacts on CO emissions

Table 6.2 presents the estimated parameters for equation 5.3. The parameters are estimated by five models, for the reasons explained in chapter 5. The equation estimated by the log-linear WLS model has the most powerful F-statistic as compared to the other four models. Furthermore, the adjusted R^2 is 92.73% for the log-linear WLS model as compared to 21.66% and 16.48% respectively for the equation estimated by log-linear and OLS models with robust errors. In the case of the majority of the parameters, the significance and direction of the estimators is in agreement for the five models. There are however some parameters on which the predicted significance and direction differ among the five models, which is mentioned in the discussion below; otherwise it is assumed that the models are in agreement. The predicted magnitude of the estimators is different in OLS, box-cox, log-linear, WLS and robust regression

---

[96] The constant in the estimated equations 5.3-5.5 represents the mean emission factor in grams/gallon for the reference group of vehicles, which is a 1997 model year passenger car manufactured by Ford in the USA that was observed inside the 13 county area in 1997 and belongs to the initial test/initial pass control fleet. The constant should be adjusted for more realistic interpretation by exogenously specifying the parametric constraints representing the technological parameters and physical conditions at the time of measurement.

[97] Formally, the coefficient values should be raised by a power equal to the inverse of the estimated lambda value in the Box-Cox model, which gives Box-Cox regression estimates in terms of change in emission factors in response to a unit change in the independent parameters. In the case of Box-Cox regression on HC emission factors, a likelihood ratio test could not reject the null hypothesis that lambda is equal to zero. So results in table 6.3 show very similar values for Box-Cox and log-linear predicted coefficients, though their standard errors remain different. In case of HC, Box-Cox coefficients can thus be interpreted as % change. But, in the case of CO and NO, the lambda value is slightly different from zero. In the case of CO and NO, the LR test rejects the null hypothesis that lambda is equal to zero. Box-Cox regression results for CO and NO should thus be interpreted accordingly, i.e. by powering the coefficient values by the inverse of estimated lambda.

models because each model assumes a different functional specification of the estimated equation, a different weighting of the error terms and a different methodology to ascertain the estimators.

Table 6.2: Regression models predicting the effect of vehicle owners' decision behaviors on vehicular tail-pipe CO emissions measured in grams/gallon (dependent variable)

Predictors	OLS with robust errors model (N= 430,114)	Box-Cox regression model (N= 430,114)	Log-Linear model with robust errors (N= 430,114)	Log-Linear WLS model (N= 430,114)	Log-Linear Robust Regression (N= 430,114)
Constant	271.7187*** (103.4714)	3.2747 (NA)	3.6727*** (.3588)	2.6862*** (.3450)	3.0975*** (0.3539)
1998	-29.9428*** (6.2609)	-0.1270*** (0.0021)	-.1626*** (.0211)	-0.1819*** (0.0201)	-0.1710*** (0.0205)
1999	-46.6687*** (3.6889)	-0.3280*** (0.0003)	-.4056*** (.0138)	-0.4216*** (0.0139)	-0.4193*** (0.0132)
2000	-75.8648*** (3.2812)	-0.3649*** (0.0003)	-.4648*** (.0118)	-0.4812*** (0.0115)	-0.5058*** (0.0121)
2001	-113.9313*** (3.9702)	-0.5290*** (0.0002)	-.6727*** (.0143)	-0.6611*** (0.0141)	-0.7168*** (0.0142)
In-eligible fleet	33.7834*** (3.4461)	0.0542*** (0.0015)	.0723*** (.0112)	0.0554*** (0.0112)	.0696*** (.0111)
1998 In-eligible fleet	-15.3392*** (4.686)	0.0021 (0.0794)	-.0002 (.0163)	0.0141 (0.0160)	-0.0035 (0.0161)
1999 In-eligible fleet	-21.6442*** (4.4303)	-0.0608*** (0.0025)	-.0765*** (.0162)	-0.0881*** (0.0163)	-0.0949*** (0.0155)
2000 In-eligible fleet	-22.2537*** (3.9122)	-0.0099 (0.0127)	-.0153 (.0137)	-0.0044 (0.0134)	-0.0109 (0.0141)
2001 In-eligible fleet	-7.4153* (3.9553)	-0.1071*** (0.0013)	-.1250*** (.0143)	-0.1133*** (0.0137)	-0.1046*** (0.0150)
Waived fleet	164.7028*** (56.5296)	0.1147 (0.0575)	.1731 (.1142)	0.1691 (0.1177)	0.2107** (0.1022)
1998 Waived fleet	-33.2081 (76.2185)	0.1508 (0.0881)	.1753 (.1582)	0.2072 (0.1712)	0.1293 (0.1450)
1999 Waived fleet	-29.4832 (66.9679)	0.1124 (0.0875)	.1267 (.1455)	0.1404 (0.1475)	0.2051* (0.1248)
2000 Waived fleet	-199.257*** (65.6870)	-0.2222** (0.0467)	-.3111** (.1435)	-0.2999** (0.1524)	-0.4349*** (0.1282)
2001 Waived fleet	-188.9482*** (64.7084)	-0.1542 (0.0672)	-.2275 (.1457)	-0.2059 (0.1526)	-0.2355* (0.1281)
Rest-of-Georgia	70.0779*** (5.9385)	0.1118*** (0.0015)	.1498*** (.0166)	0.1372*** (0.0167)	0.1529*** (0.0161)
1998 Rest-of-Georgia	-26.1948*** (8.2247)	-0.0093 (0.0385)	-.0156 (.0246)	-0.0149 (0.0246)	-0.0135 (0.0237)
1999 Rest-of-Georgia	-36.3245*** (7.9434)	-0.0344* (0.0099)	-.0478* (.0250)	-0.0693*** (0.0255)	-0.0572** (0.0232)
2000 Rest-of-Georgia	-39.6146*** (7.0934)	-0.0075 (0.0377)	-.0160 (.0213)	-0.0073 (0.0210)	-0.0210 (0.0211)
2001 Rest-of-Georgia	-43.7554*** (7.2393)	-0.0439*** (0.0067)	-.0605*** (.0219)	-0.0573*** (0.0214)	-0.0808*** (0.0215)
Missing fleet	13.4899* (7.0051)	0.0081 (0.0339)	.0115 (.0209)	0.0022 (0.0208)	0.0025 (0.0208)
1998 Missing fleet	25.8575** (10.8767)	0.0629** (0.0096)	.0826** (.0320)	0.0907*** (0.0318)	0.1006*** (0.0309)

1999 Missing fleet	6.8725 (12.3429)	0.045 (0.0208)	.0568 (.0416)	0.0580 (0.0421)	0.0715* (0.0385)
2000 Missing fleet	-1.2608 (10.8208)	0.049* (0.0172)	.0606* (.0355)	0.0669* (0.0347)	0.0671* (0.0365)
2001 Missing fleet	-39.9980*** (11.7792)	-0.0645** (0.0136)	-.0845* (.0391)	-0.0429 (0.0393)	-0.0911** (0.0373)
Retest pass	179.8482*** (18.7191)	0.2507*** (0.0035)	.3443*** (.0395)	0.3483*** (0.0421)	0.3832*** (0.0373)
1998 Retest pass	-72.4214*** (24.7185)	-0.019 (0.0904)	-.0390 (.0555)	-0.0381 (0.0579)	-0.0610 (0.0522)
1999 Retest pass	-67.6317*** (22.9615)	0.0348 (0.0416)	.0260 (.0535)	0.0342 (0.0550)	0.0534 (0.0478)
2000 Retest pass	-130.2042*** (20.8037)	-0.0615* (0.0206)	-.1001** (.0472)	-0.1134** (0.0492)	-0.1217*** (0.0447)
2001 Retest pass	-128.8493*** (20.6150)	0.0095 (0.1264)	-.0181 (.0464)	-0.0234 (0.0490)	-0.0475 (0.0436)
Migrated pass	50.0453*** (18.6712)	0.0824* (0.0218)	.1107* (.0578)	0.1039* (0.0577)	0.0951* (0.0533)
1998 Migrated pass	Dropped	Dropped	Dropped	Dropped	Dropped
1999 Migrated pass	-18.5435 (22.1290)	0.0420 (0.0647)	.0466 (.0716)	0.0342 (0.0724)	0.0730 (0.0656)
2000 Migrated pass	-16.8888 (20.9201)	0.0141 (0.1718)	.0144 (.0659)	0.0046 (0.0653)	0.0146 (0.0619)
2001 Migrated pass	-32.0875* (21.3604)	-0.0512 (0.0511)	-.0690 (.0683)	-0.0637 (0.0681)	-0.0628 (0.0644)
Retest fail	273.6526*** (42.2957)	0.2923*** (0.0116)	.4105*** (.0820)	0.3889*** (0.0955)	0.4591*** (0.0733)
1998 Retest fail	-37.4749 (53.9025)	0.1649** (0.037)	.2000* (.1106)	0.2394** (0.1201)	0.2494** (0.0983)
1999 Retest fail	-45.7117 (55.8085)	0.2708*** (0.0237)	.3172*** (.1110)	0.3485*** (0.1228)	0.2954*** (0.1007)
2000 Retest fail	-126.4325** (53.0436)	0.0899 (0.0712)	.0917 (.1128)	0.1266 (0.1261)	0.1036 (0.1007)
2001 Retest fail	-209.1945*** (45.3615)	-0.0064 (0.709)	-.0482 (.0954)	-0.0434 (0.1069)	-0.0766 (0.0862)
Migrated fail	253.2657*** (75.9385)	0.396*** (0.0157)	.5540*** (.1359)	0.5529*** (0.1548)	0.5454*** (0.1345)
1998 Migrated fail	Dropped	Dropped	Dropped	Dropped	Dropped
1999 Migrated fail	-83.6446 (90.1828)	0.0177 (0.9822)	.0123 (.1697)	0.0058 (0.1868)	0.0927 (0.1629)
2000 Migrated fail	-116.7523 (84.1785)	0.0408 (0.2831)	-.0399 (.1606)	-0.0229 (0.1792)	-0.0277 (0.1560)
2001 Migrated fail	-118.5811 (90.9295)	-0.0024 (2.3522)	-.0480 (.1762)	-0.1150 (0.1969)	-0.0290 (0.1671)
Missing fail	105.7631** (43.1143)	0.3955*** (0.0057)	.2667** (.1043)	0.2783** (0.1103)	0.3196*** (0.0911)
1998 Missing fail	Dropped	Dropped	Dropped	Dropped	Dropped
1999 Missing fail	116.5531** (54.9200)	-0.1963** (0.0382)	.2559** (.1285)	0.2655* (0.1370)	0.3235*** (0.1090)
2000 Missing fail	-14.2597 (48.5790)	-0.1347** (0.0278)	.0723 (.1165)	0.0571 (0.1231)	0.0326 (0.1032)

2001 Missing fail	-104.098** (47.2615)	-0.2654*** (0.0143)	-.1067 (.1186)	-0.1185 (0.1268)	-0.1707* (0.1036)
Missing pass	17.3579** (8.7351)	0.0703*** (0.0048)	.0360 (.0294)	0.0266 (0.0288)	0.0265 (0.0283)
1998 Missing pass	Dropped	Dropped	Dropped	Dropped	Dropped
1999 Missing pass	.7527 (11.4038)	-0.0433 (0.0195)	.0528 (.0393)	0.0722* (0.0394)	0.0677* (0.0365)
2000 Missing pass	-20.4405** (10.0849)	-0.0568** (0.0099)	-.0193 (.0346)	-0.0029 (0.0339)	-0.0182 (0.0341)
2001 Missing pass	-21.6329** (9.8781)	-0.1335*** (0.0039)	-.1121*** (.0342)	-0.1017*** (0.0335)	-0.1195*** (0.0333)
Vehicle age (years)	4.4353*** (.6845)	0.1129*** (.000023)	.1376*** (.0021)	0.1337*** (0.0019)	0.1379*** (0.0020)
Vehicle age squared	1.9123*** (.0894)	-0.0022*** (.000013)	-.0022*** (.0002)	-0.0022*** (0.0002)	-0.0018*** (0.0002)
Vehicle age cubed	-.0450*** (.0028)	.000018*** (.0000013)	.00001 (.0000069)	.00001** (.0000067)	0.000006 (0.000006)
Vehicle type	-.9108 (1.3900)	-0.0154*** (0.0009)	-.0174*** (.0047)	-0.0437*** (0.0043)	-0.0251*** (0.0046)
GM	-6.6697*** (1.7616)	0.0109** (0.0021)	.0109* (.0061)	0.0003 (0.0058)	0.0199*** (0.0060)
CHRYSLER	-11.3583*** (2.0199)	0.0145** (0.0026)	.0132* (.0075)	0.0049 (0.0070)	0.0230*** (0.0076)
HONDA	17.4499*** (2.2222)	0.172*** (0.0003)	.2110*** (.0082)	0.2187*** (0.0078)	0.2115*** (0.0082)
TOYOTA	-11.7244*** (2.1006)	0.0431*** (0.0011)	.0481*** (.0083)	0.0469*** (0.0078)	0.0619*** (0.0086)
NISSAN	1.6263 (2.5417)	0.0601*** (0.0009)	.0715*** (.0094)	0.0751*** (0.0089)	0.0700*** (0.0094)
MAZDA	40.9322*** (3.7993)	0.165*** (0.0006)	.2063*** (.0130)	0.1977*** (0.0126)	0.2056*** (0.0126)
MITSUBISHI	4.2410 (3.6716)	0.1143*** (0.0016)	.1372*** (.0159)	0.1254*** (0.0147)	0.1447*** (0.0171)
MERCEDES	-37.5151*** (5.9218)	-0.2051*** (0.0018)	-.2537*** (.0229)	-0.2420*** (0.0209)	-0.2498*** (0.0240)
VOLVO	7.4748 (7.8128)	0.0576** (0.012)	.0716** (.0314)	0.0829*** (0.0293)	0.0932*** (0.0331)
VW	-10.7312* (6.4955)	-0.0123 (0.0282)	-.0155 (.0233)	-0.0051 (0.0222)	-0.0289 (0.0234)
ISUZU	28.7500*** (6.2926)	0.1225*** (0.0023)	.1546*** (.0218)	0.1151*** (0.0217)	0.1363*** (0.0211)
Other Manufacturers	12.6250** (5.2914)	0.0495*** (0.0035)	.0631*** (.0172)	0.0671*** (0.0160)	0.0686*** (0.0165)
JAPAN	-8.9188*** (1.7433)	-0.0709*** (0.0003)	-.0860*** (.0062)	-0.1042*** (0.0059)	-0.0947*** (0.0061)
CANADA	7.5783*** (1.8164)	0.0329*** (0.0008)	.0411*** (.0064)	0.0243*** (0.0060)	0.0453*** (0.0064)
GERMANY	-79.8773*** (4.7643)	-0.2133*** (0.0009)	-.2758*** (.0168)	-0.2877*** (0.0159)	-0.2854*** (0.0170)
MEXICO	-1.8791 (2.8195)	0.0454*** (0.0023)	.0530*** (.0120)	0.0496*** (0.0110)	0.0669*** (0.0129)
SWEDEN	-112.8849*** (6.8383)	-0.3608*** (0.0014)	-.4617*** (.0269)	-0.4443*** (0.0252)	-0.4907*** (0.0280)
KOREA	6.9760	0.0621***	.0768***	0.0314	0.0754***

	(6.5546)	(0.0053)	(.0231)	(0.0216)	(0.0227)
UK	-57.9433***	-0.2742***	-.3426***	-0.3283***	-0.3489***
	(7.2312)	(0.0028)	(.0338)	(0.0310)	(0.0347)
Other countries	-16.8513	-0.049	-.0608	-0.1096*	-0.0582
	(15.7561)	(0.0422)	(.0580)	(0.0562)	(0.0572)
AIR	42.9587***	0.0345***	.0513***	0.0527***	0.0569***
	(1.5062)	(0.0004)	(.0050)	(0.0049)	(0.0048)
TWC	-33.9468***	0.0882***	.1013**	0.1751***	0.1822***
	(14.7226)	(0.0099)	(.0399)	(0.0387)	(0.0372)
EGR	-17.4359***	-0.0884***	-.1110***	-0.1139***	-0.1165***
	(1.4657)	(0.0002)	(.0055)	(0.0051)	(0.0056)
CLL	8.0570	0.0651***	.0826***	0.0513*	0.0411
	(9.7236)	(0.0088)	(.0317)	(0.0297)	(0.0301)
TAC	89.7441***	0.2094***	.2741***	0.2840***	0.3103***
	(2.5173)	(0.0001)	(.0074)	(0.0075)	(0.0068)
OXY	9.6161	0.1481***	.1846***	0.2274***	0.2494***
	(12.5296)	(0.0027)	(.0279)	(0.0284)	(0.0252)
PCV	209.4673***	0.5245***	.6825***	0.4817***	0.7260***
	(14.0590)	(0.0021)	(.0422)	(0.0366)	(0.0418)
Ambient temperature (F)	-.2553***	0.0021***	.0022***	0.0036***	0.0015***
	(.0443)	(.0000066)	(.0001)	(0.0001)	(0.0001)
Relative humidity (%)	-.3415***	-0.0029***	-.0034***	-0.0041***	-0.0036***
	(.0310)	(.0000026)	(.0001)	(0.0001)	(0.0001)
Pressure (inches, Hg)	-11.8427***	-0.0171*	-.0230*	0.0162	-0.0023
	(3.5018)	(0.0053)	(.0121)	(0.0117)	(0.0119)
Speed (MPH)	1.4461***	0.0039***	.0051***	0.0049***	0.0042***
	(.0684)	(.0000085)	(.0002)	(0.0002)	(0.0002)
Acceleration (MPH/sec)	8.3985***	-0.0062***	-.0060**	-0.0040	-0.0258***
	(.8246)	(0.0009)	(.0030)	(0.0026)	(0.0030)
Sine (road gradient)	-8.9920***	-0.033***	-.0418***	-0.0445***	-0.0377***
	(.8061)	(0.0002)	(.0028)	(0.0026)	(0.0028)
Generation of instrument	14.7115***	-0.1040***	-.1203***	-0.1306***	-0.1588***
	(2.3764)	(0.0004)	(.0089)	(0.0086)	(0.0085)
Adj-R^2	16.48%	NA	21.66%	92.73%	NA
Root MSE	346.88	NA	1.2305	2.4366	NA
F or LR test statistic (88,430025)	494.27	102492.69	1353.22	61671.17	1544.17
Lambda	1	-.052861	0	0	0

(1) Statistics in brackets () are the standard errors of coefficients
(2) Coefficient value with one * shows significance at 90% confidence level and 10% probability of type-I error; two ** at 95% confidence level and 5% probability of type I error; and three *** at 99% confidence level and 1% probability of type I error.
(3) The Log-linear WLS model is run with no constant parameter. Rather, the weight variable is added as an explanatory variable, whose coefficient is reported in place of the constant.

The change over time in the production of CO emission-factors for the reference group vehicles is estimated through coefficients on time variables in 5 regression models presented in table 6.2. The log-linear model coefficients on time variables show that the reference group vehicles emitted 16.26%, 40.56%, 46.48% and 67.27% less emissions

in 1998, 1999, 2000 and 2001 respectively than their average 1997 levels, while holding constant vehicular characteristics and other physical conditions.[98] The coefficients on time variables also represent, *ceteris paribus*, temporal change in overall CO tailpipe emission factors. It would be fallacious to say that the coefficients on time variables represent IM program effectiveness, however, because the tailpipe emissions may also decrease due to other causes, such as changes introduced in reformulated gasoline or faster fleet turnover rate, that can also decrease the vehicular tailpipe emissions from year to year.

Given this temporal trend of decreasing CO emission factors between 1997 and 2001, the *ceteris paribus* effect of cooperative and non-cooperative decision behaviors on CO emission factors can be analyzed by a deeper scrutiny of coefficients on 10 decision variables and 40 interaction terms. The chow test rejects the null hypothesis that there is no structural change over time in CO emission factors, which is caused by decisions of vehicle owners in both control and treatment vehicle groups.[99]

Of the two cooperative fleets, the retest pass fleet vehicles were emitting 34.43% more CO emissions than the control fleet vehicles in 1997. The coefficient is significant in all of the five models. The log-linear with the robust errors model suggests that retest pass vehicles did not emit significantly less emissions from 1998 to 2001 than their 1997 levels. Only in 2000, the three log-linear models suggest about 10% to 12% reduction in CO emission factors for the retest pass vehicles.

The second cooperative fleet type, referred to as the migrated pass fleet, emitted 11.07% more CO emissions than the control fleet vehicles in 1998. The estimators on migrated pass interaction terms show that this difference was not reduced during 1999 to 2001 from its 1998 levels.

Of the four non-cooperative fleet vehicles, retest-fail vehicles are among the dirtiest CO high-emitters in all five years of the study. In 1997, retest-fail vehicles emitted 41.05% more CO emissions than the control fleet vehicles. The interaction estimators

---

[98] In the discussion below, for the purposes of brevity, I do not repeat the phrase "while holding constant vehicular characteristics and physical conditions" with every sentence, which depicts *ceteris paribus* effects. It is considered as assumed unless otherwise stated.

[99] Formally, the null hypothesis of the chow test states β_q, δ_t, $\Delta_{tq} = 0$, where q = {2,3,…,11} and t={2,3,…,5}. F-test statistic for (50,430025) degrees of freedom is estimated at 84.40 [Prob > F = 0.0000] for the OLS with robust errors model and 185.59 [Prob > F = 0.0000] for the log-linear model in table 6.2. Both OLS with robust errors and log-linear models thus reject the null hypothesis of the chow test.

involving retest fail vehicles clearly show, especially for the log-linear model, that the CO emission factors of retest-fail vehicles in 2000 and 2001 are statistically not different from its 1997 level. In 1998 and 1999, as per WLS model, retest fail vehicles emitted 23.94% and 34.85% higher CO emission factors than their 1997 level difference. Retest fail vehicles thus also emitted higher emissions than the retest pass vehicles in all the five years of the study. Further, instead of decreasing the emission factors for the retest-fail vehicles, their emissions either did not decrease, or even increased.

The second non-cooperative fleet, migrated fail vehicles are also among the dirtiest CO high-emitting vehicles. In 1998, migrated fail vehicles, on average, emitted 55.40% more CO than the control fleet vehicles. This difference did not decrease during 1999 to 2001.

The third non-cooperative fleet, missing fail fleet vehicles, are also significantly higher in CO emissions than the control fleet vehicles. In 1998, missing fail fleet vehicles, on average, emitted 26.67% higher CO than the control fleet vehicles. This difference did not significantly decrease during 2000 to 2001. However, in 1999, missing fail vehicles were emitting 25.59% higher CO emissions than their 1998 levels.

The fourth non-cooperative fleet, missing pass vehicles, did not produce significantly higher CO emissions than the control fleet vehicles in 1998. The log-linear model suggests that this difference remained at 0% during the years 1999 to 2000 and showed an 11% reduction in 2001. The log-linear WLS model however shows a 7.22% increase in CO emissions of missing pass vehicles in 1999 as compared to their 1998 levels.

For CO emission factors, the null hypothesis [H_2] states: The difference between the CO emissions of cooperative and non-cooperative vehicle owners is not significantly different than zero. While it is possible to test this hypothesis for each year of the study, here I present the results for 5 years of the study period, taken together. This null hypothesis is tested by employing an F-test after estimating the equation 5.3 for each of the five regression models. Here the results from log-linear with robust errors model are reported. Formally, the null hypothesis is stated as follows:[100]

---

[100] Note that equation 6.1 does not have 4 parameters that represent migrated pass fleet [$\Delta_{2,7}$] among the cooperative types; and migrated fail fleet [$\Delta_{2,9}$], missing fail fleet [$\Delta_{2,10}$] and missing pass fleet [$\Delta_{2,11}$] among the non-cooperative types in the year 1997. No vehicles in the 1997 remote sensing sample were found in these four treatment groups. 1997 is an exception because

(6.1) $[\beta_6 + \beta_7 + \Delta_{2,6} + \Delta_{3,6} + \Delta_{4,6} + \Delta_{5,6} + \Delta_{3,7} + \Delta_{4,7} + \Delta_{5,7}]/9 = [\beta_8 + \beta_9 + \beta_{10} + \beta_{11} + \Delta_{2,8} + \Delta_{3,8} + \Delta_{4,8} + \Delta_{5,8} + \Delta_{3,9} + \Delta_{4,9} + \Delta_{5,9} + \Delta_{3,10} + \Delta_{4,10} + \Delta_{5,10} + \Delta_{3,11} + \Delta_{4,11} + \Delta_{5,11}]/17$, where 9 and 17 respectively represent the number of parameters for cooperative and non-cooperative vehicle groups in estimated equation 5.3, as presented in table 6.2.

For equation 6.1, the F-test statistic with (1,430025) degrees of freedom is estimated to be 4.63 [Prob > F = 0.0315]. The log-linear model cannot reject the null hypothesis [H_2]. We can thus state that, on average, there is no statistical difference between the CO emission factors of cooperative and non-cooperative vehicles in the Atlanta airshed. This is a surprising result because I expected cooperative vehicles to emit on average less CO emissions than those of non-cooperative vehicles.

The explanation for this surprising result resides in three factors: First, the standard errors of CO emissions for cooperative and non-cooperative vehicles are so large that the F test does not distinguish any difference between their means. Second, the repairs on emission control systems for CO might not be durable enough, and the cooperative vehicles, which pass the retests, actually have faster deterioration of repairs on their emission control systems. Third, the empirically estimated cooperative vehicle owners may be *actually* non-cooperative types because the apparently cooperative vehicles might have been falsely passed in IM emissions retests or they might have employed fraudulent repairs on emissions control systems before appearing in retests and securing pass in emissions test.

6.3.2: Impacts on HC emissions

Table 6.3 presents the estimated parameters for equation 5.4. The log-linear WLS model has the most powerful F-statistic as compared to the other three models. The adjusted R^2 is 84.12% for the log-linear WLS model as compared to 49.31% and 8.52% respectively for the log-linear and OLS models with robust errors.

In table 6.3, the coefficients on time variables show that vehicles emitted 16.75%, 42.21%, 57.81% and 105.15% less HC emissions in 1998, 1999, 2000 and 2001 respectively than their average 1997 levels. Thus, overall, HC emissions have been drastically reduced from 1997 to 2001, which can be attributed to some combination of IM program effectiveness, changes in reformulated gasoline, as well as faster fleet turn-over rates in the Atlanta airshed during the study period.

it was the first year of the "enhanced" IM program and no vehicles in these four categories were matched with the "basic" IM program data that wad collected in Atlanta in 1995 and 1996.

Table 6.3: Regression models predicting the effect of vehicle owners' decision behaviors on vehicular tail-pipe HC emissions measured in grams/gallon (dependent variable)

Predictors	OLS with robust errors model (N= 430,114)	Box-Cox regression model (N= 430,114)	Log-Linear model with robust errors (N= 430,114)	Log-Linear WLS model (N= 430,114)	Log-Linear Robust Regression (N= 430,114)
Constant	153.5709***	4.15002	4.1513***	3.9142***	4.3192***
	(13.5168)	(NA)	(0.2650)	(0.2686)	(0.2534)
1998	-9.9466***	-0.1675***	-0.1675***	-0.1660***	-0.1106***
	(.9668)	(0.0016)	(0.0160)	(0.0164)	(0.0147)
1999	-15.4118***	-0.422***	-0.4221***	-0.4016***	-0.3522***
	(.6521)	(0.0003)	(0.0098)	(0.0107)	(0.0094)
2000	-16.3537***	-0.578***	-0.5781***	-0.5756***	-0.4087***
	(.5964)	(0.0002)	(0.0098264)	(0.0098)	(0.0087)
2001	-20.2945***	-1.0513***	-1.0515***	-1.0206***	-0.9161***
	(.6031)	(0.0001)	(0.0123)	(0.0122)	(0.0101)
In-eligible fleet	2.9642***	0.0525***	.0525***	0.0484***	.0448***
	(.6952)	(0.0015)	(.0091)	(0.0098)	(.0080)
1998 In-eligible fleet	-1.9033**	0.0025	0.0025	0.0053	0.0092
	(.8382)	(0.0632)	(0.0122)	(0.0132)	(0.0115)
1999 In-eligible fleet	-2.8775***	-0.0572***	-0.0572***	-0.0698***	-0.0515***
	(.7671)	(0.0026)	(0.0114)	(0.0123)	(0.0110)
2000 In-eligible fleet	-2.3625***	-0.0252**	-0.0252**	-0.0300***	-0.0203**
	(.7133)	(0.0049)	(0.0116)	(0.0114)	(0.0101)
2001 In-eligible fleet	-0.7420	-0.259***	-0.259***	-0.2379***	-0.2538***
	(.7071)	(0.0005)	(0.0124)	(0.0150)	(0.0107)
Waived fleet	32.6631***	0.1574*	0.1575	0.1415	0.0926
	(12.7499)	(0.0413)	(0.1012)	(0.1003)	(0.0732)
1998 Waived fleet	-34.5108**	-0.217*	-0.2171*	-0.1976	-0.1350
	(13.3225)	(0.0602)	(0.1274)	(0.1302)	(0.1038)
1999 Waived fleet	-19.5944	0.0876	0.0876	0.0784	0.1242
	(13.5980)	(0.1104)	(0.1164)	(0.1144)	(0.0893)
2000 Waived fleet	-33.0702**	-0.1247	-0.1248	-0.1179	-0.0690
	(13.0477)	(0.0819)	(0.1207)	(0.1158)	(0.0918)
2001 Waived fleet	-38.0835***	0.1176	0.1174	0.1170	0.2857***
	(12.8037)	(0.0868)	(0.1310)	(0.1294)	(0.0917)
Rest-of-Georgia	6.8578***	0.0963***	0.0963***	0.0944***	0.0903***
	(1.0851)	(0.0017)	(0.0138)	(0.0149)	(0.0115)
1998 Rest-of-Georgia	-2.8641**	-0.0203	-0.0203	-0.0145	-0.0277
	(1.3847)	(0.0173)	(0.0188)	(0.0203)	(0.0170)
1999 Rest-of-Georgia	-5.7092***	-0.07***	-0.0700***	-0.0850***	-0.0765***
	(1.2352)	(0.0048)	(0.0176)	(0.0190)	(0.0166)
2000 Rest-of-Georgia	-6.6681***	-0.0515***	-0.0515***	-0.0376**	-0.0588***
	(1.1322)	(0.0054)	(0.0179)	(0.0176)	(0.0151)
2001 Rest-of-Georgia	-7.4047***	-0.0492***	-0.0492***	-0.0687***	-0.0400***
	(1.0982)	(0.0059)	(0.0190)	(0.0194)	(0.0154)
Missing fleet	.7310	0.0042	0.0042	0.0006	0.0103
	(1.2414)	(0.0639)	(0.0172)	(0.0186)	(0.0149)
1998 Missing fleet	3.7458**	0.0549**	0.0549**	0.0655***	0.0473**
	(1.8152)	(0.0108)	(0.0242)	(0.0255)	(0.0221)
1999 Missing fleet	0.2544	0.0356	0.0355	0.0385	0.0303
	(1.7741)	(0.026)	(0.0276)	(0.0300)	(0.0276)
2000 Missing fleet	0.6060	0.0245	0.0245	0.0270	0.0042
	(1.4891)	(0.0338)	(0.0309)	(0.0288)	(0.0261)
2001 Missing	-3.8399***	0.0618**	0.0617*	0.0839**	0.0548**

fleet	(1.2890)	(0.014)	(0.0337)	(0.0330)	(0.0267)
Retest pass	6.6370***	0.1202***	0.1203***	0.1235***	0.1916***
	(2.2354)	(0.0072)	(0.0317)	(0.0336)	(0.0267)
1998 Retest pass	-0.1160	-0.0688*	-0.0688	-0.0683	-0.1564***
	(3.1877)	(0.0246)	(0.0427)	(0.0450)	(0.0373)
1999 Retest pass	-1.3334	0.0324	0.0324	0.0145	-0.0631*
	(2.5936)	(0.0439)	(0.0391)	(0.0414)	(0.0342)
2000 Retest pass	-5.7568**	0.0677*	0.0677*	0.0546	-0.0178
	(2.3470)	(0.0184)	(0.0374)	(0.0380)	(0.0320)
2001 Retest pass	-8.8900***	0.3719***	0.3718***	0.3805***	0.3202***
	(2.2482)	(0.0032)	(0.0379)	(0.0392)	(0.0312)
Migrated pass	-.3243	0.1108***	0.1108***	0.1058***	0.1397***
	(1.4433)	(0.0159)	(0.0359)	(0.0409)	(0.0381)
1998 Migrated pass	(Dropped)	(Dropped)	(Dropped)	(Dropped)	(Dropped)
1999 Migrated pass	1.520688	-0.0868*	-0.0867**	-0.1054**	-0.1334***
	(1.9620)	(0.0308)	(0.043)	(0.0495)	(0.0469)
2000 Migrated pass	1.5995	-0.0547	-0.0547	-0.0572	-0.0933**
	(1.6211)	(0.0435)	(0.0451)	(0.0468)	(0.0443)
2001 Migrated pass	0.0845	-0.0356	-0.0355	-0.0449	-0.0486
	(1.5098)	(0.0726)	(0.0484)	(0.0510)	(0.0461)
Retest fail	15.4359**	0.1175**	0.1175*	0.1258*	0.1361***
	(6.2990)	(0.0285)	(0.0695)	(0.0690)	(0.0525)
1998 Retest fail	-1.8161	0.1351*	0.1351	0.1323	0.1237*
	(7.4912)	(0.0444)	(0.0888)	(0.0902)	(0.0703)
1999 Retest fail	-4.3512	0.2008**	0.2008**	0.1743**	0.1589**
	(7.2060)	(0.0314)	(0.0886)	(0.0870)	(0.0721)
2000 Retest fail	-2.6538	0.2349***	0.2348**	0.2165**	0.1891***
	(7.8656)	(0.0268)	(0.0972)	(0.0873)	(0.0721)
2001 Retest fail	-15.4762**	0.4094***	0.4093***	0.4074***	0.3776***
	(6.3302)	(0.0113)	(0.0819)	(0.0799)	(0.0617)
Migrated fail	.8884	0.5874***	-0.0198	0.6007***	-0.0175
	(6.1949)	0.0104	(0.1048)	(0.0875)	(0.0963)
1998 Migrated fail	Dropped	-0.6073	(Dropped)	-0.6060***	(Dropped)
		-0.0286		(0.1363)	
1999 Migrated fail	-0.2665	-0.4787***	0.1286	-0.5145***	0.1450
	(7.0595)	(-0.0238)	(0.1234)	(0.1081)	(0.1166)
2000 Migrated fail	0.5434	-0.2691***	0.3382***	-0.2795***	0.3214***
	(6.5291)	(0.0372)	(0.1231)	(0.1042)	(0.1117)
2001 Migrated fail	-4.7351	(Dropped)	0.6072***	(Dropped)	0.5996***
	(6.2625)		(0.1376)		(0.1196)
Missing fail	4.6306	0.1777***	0.0525	0.0715	0.0530
	(4.6645)	0.0126	(0.0710)	(0.0701)	(0.0652)
1998 Missing fail	Dropped	-0.1253	(Dropped)	(Dropped)	(Dropped)
		(0.059)			
1999 Missing fail	1.6664	(Dropped)	0.1252	0.0881	0.1180
	(5.5262)		(0.0855)	(0.0864)	(0.0780)
2000 Missing fail	-3.9839	-0.0075	0.1177	0.1023	0.1304*
	(4.9116)	(0.4994)	(0.0820)	(0.0789)	(0.0739)
2001 Missing fail	-8.7540*	0.2319***	0.3571***	0.3844***	0.4102***
	(4.7124)	(0.0161)	(0.0871)	(0.0863)	(0.0741)
Missing pass	-.1192	0.031*	0.0407**	0.0470**	0.0519**
	(.9926)	0.0106	(0.0196)	(0.0217)	(0.0203)
1998 Missing pass	Dropped	0.0097	(Dropped)	(Dropped)	(Dropped)
		(0.0857)			

1999 Missing pass	1.9696 (1.3228)	(Dropped)	-0.0096 (0.0253)	-0.0205 (0.0280)	-0.0276 (0.0261)
2000 Missing pass	0.3655 (1.0795)	0.02 (0.0276)	0.0103 (0.0249)	-0.00002 (0.0253)	-0.0182 (0.0244)
2001 Missing pass	-0.5974 (1.0014)	-0.0353 (0.0147)	-0.0449* (0.025207)	-0.0565** (0.0263)	-0.0560** (0.0238)
Vehicle age (years)	-0.4019*** (.0829)	0.0205*** (0.0001)	0.0205*** (0.0016)	0.0139*** (0.0015)	0.0206*** (0.0014)
Vehicle age squared	0.1560*** (.0097)	0.0041*** (.000007)	0.0040*** (0.0001)	0.0046*** (0.0001)	0.0038*** (0.0001)
Vehicle age cubed	-0.003*** (.0003)	-0.0001*** (.0000002)	-0.0001*** (0.0000057)	-0.0001*** (0.0000055)	-0.0001*** (0.0000044)
Vehicle type	-0.8933*** (.1727)	-0.0304*** (0.0004)	-0.0303*** (0.0036)	-0.0393*** (0.0035)	-0.0267*** (0.0033)
GM	0.2484 (.2251)	0.0202*** (0.0011)	0.0201*** (0.0049)	0.0225*** (0.0047)	0.0171*** (0.0043)
CHRYSLER	-1.7020*** (.2447)	-0.0118** (0.0031)	-0.0118** (0.0060)	-0.0086 (0.0057)	-0.0121** (0.0055)
HONDA	-0.2596 (.3114)	-0.0759*** (0.0006)	-0.0759*** (0.0065)	-0.0603*** (0.0062)	-0.0972*** (0.0059)
TOYOTA	0.2723 (.2971)	-0.0238*** (0.0019)	-0.0238*** (0.0068)	-0.0123* (0.0064)	-0.0351*** (0.0061)
NISSAN	0.1181 (.3404)	0.0078 (0.0071)	0.0078 (0.0074)	0.0196*** (0.0071)	-0.0080 (0.0067)
MAZDA	0.5279 (.4296)	0.067*** (0.0015)	0.0670*** (0.0101)	0.0787*** (0.0098)	0.0591*** (0.0090)
MITSUBISHI	1.3831** (.5694)	0.1224*** (0.0015)	0.1224*** (0.0134)	0.1205*** (0.0131)	0.1082*** (0.0122)
MERCEDES	-2.0218** (.7926)	-0.0316* (0.0113)	-0.0316* (0.0191)	-0.0215 (0.0186)	-0.0191 (0.0171)
VOLVO	-0.9530 (1.1722)	-0.0064 (0.1066)	-0.0064 (0.0245)	0.0040 (0.0251)	0.0024 (0.0237)
VW	-0.4414 (.8383)	0.0307* (0.0111)	0.0306 (0.0189)	0.0391** (0.0183)	0.0356** (0.0167)
ISUZU	0.7610 (.7141)	-0.0132 (0.0211)	-0.0132 (0.0171)	-0.0129 (0.0164)	-0.0403** (0.0151)
Other Manufacturers	0.1011 (.7064)	-0.0121 (0.014)	-0.0121 (0.0131)	-0.0021 (0.0130)	-0.0265** (0.0118)
JAPAN	-0.9638*** (.2396)	-0.0451*** (0.0005)	-0.0450*** (0.0047)	-0.0472*** (0.0046)	-0.0465*** (0.0044)
CANADA	-0.4041* (.2269)	0.02*** (0.0013)	0.0200*** (0.0050)	0.0187*** (0.0049)	0.0232*** (0.0046)
GERMANY	-1.5283** (.7085)	-0.123*** (0.0015)	-0.1230*** (0.0131)	-0.1169*** (0.0133)	-0.1309*** (0.0122)
MEXICO	0.2090 (.4372)	-0.0052 (0.02)	-0.0052 (0.0098)	-0.0082 (0.0098353)	-0.0097 (0.0092)
SWEDEN	-3.1622*** (1.1022)	-0.1912*** (0.0026)	-0.1912*** (0.0205)	-0.1903*** (0.0220)	-0.2071*** (0.0200)
KOREA	4.1963*** (1.0899)	0.1318*** (0.0024)	0.1318*** (0.0185)	0.1125*** (0.0183)	0.1329*** (0.0163)
UK	-1.9170** (.8828)	-0.1546*** (0.0049)	-0.1546*** (0.0262)	-0.1306*** (0.0245)	-0.1473*** (0.0248)
Other countries	5.3949* (3.1838)	0.1088** (0.0187)	0.1088** (0.0494)	0.1329*** (0.0490)	0.0959** (0.0410)
AIR	0.9194***	0.0578***	0.0577***	0.0590***	0.0582***

	(.1937)	(0.0003)	(0.0038)	(0.0037)	(0.0034)
TWC	-6.6569***	-0.0518*	-0.0517	-0.0640**	0.0019
	(2.3160)	(0.0166)	(0.0323)	(0.0313)	(0.0266)
EGR	-0.9174***	-0.0462***	-0.0461***	-0.0468***	-0.0443***
	(.2011)	(0.0004)	(0.0043)	(0.0042)	(0.0040)
CLL	-5.983***	0.0198	0.0197	0.0322	0.0003
	(1.3412)	(0.0286)	(0.0246)	(0.0239)	(0.0215)
TAC	2.8398***	0.0771***	0.0770***	0.0807***	0.0723***
	(.3077)	(0.0004)	(0.0055)	(0.0054)	(0.0048)
OXY	-6.3493***	-0.0227	-0.0226	-0.0287	0.0166
	(2.0554)	(0.0174)	(0.0238)	(0.0229)	(0.0180)
PCV	17.0810***	0.0791**	0.0792**	0.0899***	0.0524*
	(2.2285)	(0.0138)	(0.0345)	(0.0337)	(0.0299)
Ambient temperature (F)	-0.0574***	-0.0008***	-0.0008***	-0.0010***	0.0002**
	(.0060)	0	(0.0001)	(0.0001)	(0.0001)
Relative humidity (%)	-0.0280***	-0.0008	-0.0008***	-0.0015***	-0.0007***
	(.0040)	0	(0.00008)	(0.00008)	(0.00007)
Pressure (inches, Hg)	-4.8235***	-0.0662	-0.0662***	-0.0562***	-0.0781***
	(.4518)	-0.0013	(0.0089)	(0.0090)	(0.0085)
Speed (MPH)	0.4391***	0.0088***	0.0088***	0.0088***	0.0078***
	(.0103)	(.000009)	(0.0001)	(0.0001)	(0.0001)
Acceleration (MPH/sec)	-0.9637***	-0.0587***	-0.0587***	-0.0445***	-0.0451***
	(.0630)	(0.0001)	(0.0026)	(0.0024)	(0.0021)
Sine (road gradient)	0.8851***	0.0128***	0.0128***	0.0063***	0.0018
	(.0967)	(0.0004)	(0.0022)	(0.0021)	(0.0020)
Generation of instrument	-7.1122***	-1.1946***	-1.1948	-1.2258***	-1.1343***
	(.1225)	(.00003)	(0.0079)	(0.0074)	(0.0061)
Adj-R^2	08.52%	NA	49.31%	84.12%	NA
Root MSE	45.959	NA	.96919	1.9217	NA
F or LR test (88,430025)	557.44	287906.67	4116.27	24751.48	4989.16
Lambda	1	-.0001259	0	0	0

1) Statistics in brackets () are the standard errors of coefficients
2) Coefficient value with one * shows significance at 90% confidence level and 10% probability of type-I error; two ** at 95% confidence level and 5% probability of type I error; and three *** at 99% confidence level and 1% probability of type I error.
3) The Log-linear WLS model is run with no constant parameter. Rather, the weight variable is added as an explanatory variable, whose coefficient is reported in place of the constant.

Given this temporal trend of decreasing HC emission factors between 1997 and 2001, the *ceteris paribus* effect of cooperative and non-cooperative decision behaviors on HC emission factors is computed by the coefficients on the interactions terms in table 6.3. The chow test rejects the null hypothesis that there is no structural change over time in HC emission factors, which is caused by decisions of vehicle owners in both control and treatment groups.[101]

---

[101] Formally, null hypothesis of the chow test states β_q, δ_t, $\Delta_{tq} = 0$, where q = {2,3,…,11} and t={2,3,…,5}. F-test statistic for (50,430025) degrees of freedom is estimated at 125.47 [Prob > F = 0.0000] for the OLS with robust errors model and 459.67 [Prob > F = 0.0000] for the log-linear

Of the two apparently cooperative fleets, retest pass fleet vehicles were emitting 12.03% more HC emissions than the control fleet vehicles in 1997. The coefficient is significant in all of the five models. There was no difference in HC emissions of retest pass vehicles between 1997, 1998 and 1999. The log-linear with robust errors model suggests that retest pass vehicles emitted 6.77% more emissions in 2000 than their 1997 levels. In 2001, the HC emissions of retest pass fleet vehicles increased even further by 37.18% as compared to their difference of 12.03% in 1997.

The log-linear model suggests that migrated passed vehicles emitted 11.8% higher HC emission factors than the control fleet vehicles in 1998, 2000 and 2001, while the difference was reduced by 8.67% in 1999.

Of the four non-cooperative fleet vehicles, the retest-fail vehicles emitted 11.75% more HC emissions than the control fleet vehicles in 1997. The interaction estimators involving retest fail vehicles show that the HC emission factors of retest-fail vehicles in 1998 and 1999 are statistically not different from their 1997 levels. In 2000 and 2001, one of the most important results of this study, the interaction terms involving retest fail fleet vehicles show that the difference in the HC emission factors of retest fail vehicles with the control fleet vehicles increased by 33.82% and 60.72% respectively over their 1997 levels. Thus, against the temporal trend of decreasing HC emissions, the retest fail vehicles are emitting HC emissions at an increasing rate. The last two results are important because they justify further attempts to more effectively address the problem of chronically high-emitting vehicles. The same applies to migrated fail and missing fail vehicles.

In 1998 and 1999, migrated fail and missing fail vehicles, on average, emitted similar HC emissions as the control fleet vehicles. However, as the log-linear model shows, the difference between the HC emissions of the migrated fail vehicles and the control fleet vehicles was 33.82% and 60.72% higher in 2000 and 2001 as compared to the 1998 level (when there was no difference). Similarly, the difference between the HC emissions of the missing fail vehicles and the control fleet vehicles was 35.71% higher in 2001 as compared to the 1998 level (when there was no difference). The HC emissions from the migrated fail and missing fail vehicles are thus also increasing over time, against the temporal trend of decreasing HC emission factors for control group vehicles.

model in table 6.3. Both OLS with robust errors and log-linear models thus reject the null hypothesis of the chow test.

The fourth non-cooperative fleet, missing pass vehicles, as per the log-linear model, produced 4.07% higher HC emissions than the control fleet vehicles in 1998. The log-linear model suggests that missing pass vehicles emitted about 4% higher HC emissions in 1998, 1999 and 2000 as compared to the control fleet vehicles, but this difference disappeared in 2001.

For HC emission factors, the null hypothesis [H_2] states: The difference between the HC emissions of cooperative and non-cooperative vehicle owners is not significantly different than zero. While it is possible to test this hypothesis for each year of the study, here I present the results for 5 years of the study period, taken together. This null hypothesis is tested by employing an F-test after estimating equation 5.4 for each of the five regression models. Here the results from log-linear model are reported. Formally, the null hypothesis is stated as follows:[102]

(6.2) $[\beta_6 + \beta_7 + \Delta_{2,6} + \Delta_{3,6} + \Delta_{4,6} + \Delta_{5,6} + \Delta_{3,7} + \Delta_{4,7} + \Delta_{5,7}]/9 = [\beta_8 + \beta_9 + \beta_{10} + \beta_{11} + \Delta_{2,8} + \Delta_{3,8} + \Delta_{4,8} + \Delta_{5,8} + \Delta_{3,9} + \Delta_{4,9} + \Delta_{5,9} + \Delta_{3,10} + \Delta_{4,10} + \Delta_{5,10} + \Delta_{3,11} + \Delta_{4,11} + \Delta_{5,11}]/17$, where 9 and 17 respectively represent the number of parameters for cooperative and non-cooperative vehicle groups in estimated equation 5.4, as presented in table 6.3.

For equation 6.2, the F-test statistic with (1,430025) degrees of freedom is estimated to be 18.01 [Prob > F = 0.0000]. The log-linear model rejects the null hypothesis of equation 6.2 and predicts there is a statistical difference between the HC emission factors of cooperative and non-cooperative vehicles. In order to estimate the direction and magnitude of this difference, the alternative hypothesis that cooperative vehicles emit less HC emissions than the non-cooperative vehicles by a factor of (1-k)% was tested. Formally,

(6.3) $[\beta_6 + \beta_7 + \Delta_{2,6} + \Delta_{3,6} + \Delta_{4,6} + \Delta_{5,6} + \Delta_{3,7} + \Delta_{4,7} + \Delta_{5,7}]/9 = k*[\beta_8 + \beta_9 + \beta_{10} + \beta_{11} + \Delta_{2,8} + \Delta_{3,8} + \Delta_{4,8} + \Delta_{5,8} + \Delta_{3,9} + \Delta_{4,9} + \Delta_{5,9} + \Delta_{3,10} + \Delta_{4,10} + \Delta_{5,10} + \Delta_{3,11} + \Delta_{4,11} + \Delta_{5,11}]/17$, where k is a rescaling parameter between the value of 0 and 1.

While the null hypothesis presented in equation 6.3 was rejected by the log-linear model for the values of k between 0.54 and 1, it was not able to reject the null

---

[102] Again, equation 6.2 does not have 4 parameters that represent migrated pass fleet [$\Delta_{2,7}$] among the cooperative types; and migrated fail fleet [$\Delta_{2,9}$], missing fail fleet [$\Delta_{2,10}$] and missing pass fleet [$\Delta_{2,11}$] among the non-cooperative types in the year 1997. No vehicles in the 1997 remote sensing sample were found in these four treatment groups. 1997 is an exception because it was the first year of the "enhanced" IM program and no vehicles in these four categories were matched with the "basic" IM program data that was collected in Atlanta in 1995 and 1996.

hypothesis for the value of k at 0.53 and below at 95% confidence level. It can therefore be concluded that the cooperative vehicles emitted at least 47% less HC emissions as compared to non-cooperative vehicles during the study period in the Atlanta airshed.

6.3.3: Impacts on NOx emissions

Table 6.4 presents the estimated parameters for equation 5.5. The log-linear WLS model has the most powerful F-statistic as compared to the other four models. The adjusted R^2 is 80.40% for the log-linear WLS model as compared to 23.21% and 20.07% for the log-linear and OLS models with robust errors.

Table 6.4: Regression models predicting the effect of vehicle owners' decision behaviors on vehicular tail-pipe NO emissions measured in grams/gallon (dependent variable)

Predictors	OLS with robust errors model (N= 86,588)	Box-Cox regression model (N= 86,588)	Log-Linear model with robust errors (N= 86,588)	Log-Linear WLS model (N= 86,588)	Log-Linear Robust Regression (N= 86,588)
Constant	14.3815	2.0026	1.6264	1.3524	1.2920
	(27.0446)	(NA)	(1.2180)	(1.1868)	(1.1853)
2000	0.7819	0.0074	-0.0103	-0.0252	0.0130
	(.8058)	(0.3709)	(0.0380)	(0.0375)	(0.0370)
2001	-4.3586***	-0.3805***	-0.2801***	-0.2961***	-0.2642***
	(.6851)	(0.0053)	(0.0325)	(0.0322)	(0.0316)
In-eligible fleet	2.8728***	0.1188**	0.0588	.0472	.0886**
	(.8178)	(0.0248)	(0.0392)	(.0392)	(.0381)
2000 In-eligible fleet	0.8151	0.0928	0.0847*	0.0962**	0.0519
	(.9628)	(0.0431)	(0.0456)	(0.0453)	(0.0444)
2001 In-eligible fleet	2.5430***	0.0945	0.0579	0.0718*	0.0354
	(.8526)	(0.0354)	(0.0417)	(0.0417)	(0.0406)
Waived fleet	6.0180	0.6404	0.4459	0.5067	0.3505
	(11.0470)	(0.6842)	(0.4785)	(0.3184)	(0.4656)
2000 Waived fleet	13.3109	0.1591	0.0414	-0.0668	0.0897
	(13.7913)	(3.4591)	(0.5370)	(0.3849)	(0.5226)
2001 Waived fleet	4.4731	-0.2019	-0.1678	-0.2190	-0.0909
	(11.615)	(2.2681)	(0.4882)	(0.3342)	(0.4751)
Rest-of-Georgia	4.1017***	0.2231**	0.1402**	0.1156*	0.1558**
	(1.5190)	(0.0353)	(0.0641)	(0.0676)	(0.0624)
2000 Rest-of-Georgia	0.3125	-0.0221	-0.0150	0.0066	-0.0279
	(1.7960)	(0.48)	(0.0741)	(0.0768)	(0.0721)
2001 Rest-of-Georgia	0.3985	-0.0187	-0.0182	0.0190	-0.0179
	(1.5764)	(0.4561)	(0.0665)	(0.0700)	(0.0647)
Missing fleet	7.8823**	0.3606**	0.2370**	0.2221*	0.2214**
	(3.2607)	(0.0694)	(0.1143)	(0.1179)	(0.1112)
2000 Missing fleet	-5.3981*	-0.1654	-0.0923	-0.0722	-0.1241
	(3.8306)	(0.2483)	(0.1464)	(0.1465)	(0.1425)
2001 Missing fleet	-7.1812***	-0.4184**	-0.2921**	-0.2806**	-0.2606**
	(3.4076)	(0.0663)	(0.1203)	(0.1245)	(0.1171)
Retest pass	18.1186***	0.6585***	0.3542***	0.3647**	0.5458***
	(4.0004)	(0.0432)	(0.1219)	(0.1481)	(0.1186)
2000 Retest	-2.0689	0.0265	0.0622	0.0539	-0.1199

pass	(4.6706)	(1.4732)	(0.1410)	(0.1606)	(0.1372)
2001 Retest pass	0.5142	0.2325	0.2013	0.1930	0.0307
	(4.0906)	(0.1281)	(0.1247)	(0.1502)	(0.1213)
Migrated pass	7.4940*	0.5623**	0.3567*	0.3217	0.4205**
	(4.5069)	(0.1329)	(0.1975)	(0.2153)	(0.1922)
2000 Migrated pass	-3.2503	-0.2876	-0.1709	-0.1289	-0.2511
	(4.9759)	(0.3044)	(0.2138)	(0.2265)	(0.2081)
2001 Migrated pass	-5.0844	-0.5106*	-0.3387*	-0.2852	-0.3905**
	(4.6326)	(0.1537)	(0.2025)	(0.2198)	(0.1970)
Retest fail	26.2440*	1.0229***	0.6158**	0.5749	0.7848***
	(13.7208)	(0.1677)	(0.2994)	(0.4216)	(0.2913)
2000 Retest fail	-2.9820	0.0192	0.0319	0.0805	-0.2199
	(16.1268)	(19.1565)	(0.3740)	(0.4801)	(0.3639)
2001 Retest fail	-9.0604	-0.183	-0.0818	-0.0358	-0.2522
	(13.8330)	(0.9681)	(0.3040)	(0.4244)	(0.2959)
Migrated fail	9.2957	0.1871	0.1004	0.1800	0.0106
	(20.0905)	(2.0559)	(0.4483)	(0.5523)	(0.4363)
2000 Migrated fail	-0.8451	0.1966	0.1443	0.0208	0.1745
	(21.2589)	(2.427)	(0.4996)	(0.6015)	(0.4861)
2001 Migrated fail	5.1742	0.4529	0.2872	0.1888	0.4163
	(20.4262)	(0.9057)	(0.4630)	(0.5652)	(0.4505)
Missing fail	3.4762	0.2177	0.1408	0.1235	0.2163
	(6.5172)	(0.547)	(0.2495)	(0.3004)	(0.2428)
2000 Missing fail	10.9541	0.343	0.1944	0.2069	0.1483
	(8.9139)	(0.4838)	(0.2945)	(0.3247)	(0.2866)
2001 Missing fail	6.0114	0.0884	0.0277	0.0469	0.0001
	(6.8279)	(1.4263)	(0.2562)	(0.3084)	(0.2493)
Missing pass	4.3447**	0.266**	0.1718**	0.1776**	0.1811**
	(2.0723)	(0.0502)	(0.0835)	(0.0867)	(0.0812)
2000 Missing pass	-2.3342	-0.2204	-0.1494	-0.1397	-0.1622
	(2.5718)	(0.0891)	(0.1013245)	(0.1039)	(0.0985)
2001 Missing pass	-5.9539***	-0.4598***	-0.3175***	-0.3171***	-0.3118***
	(2.1266)	(0.0309)	(0.0861)	(0.0894)	(0.0838)
Vehicle age (years)	4.9480***	0.4659***	0.3361***	0.3385***	0.3452***
	(.1473)	(0.0001)	(0.0055)	(0.0054)	(0.0053)
Vehicle age squared	-0.1319***	-0.0206***	-0.0156***	-0.0158***	-0.0160***
	(.0169)	(.00002)	(0.0005)	(0.0005)	(0.0005)
Vehicle age cubed	-0.00007	0.0002***	0.0001***	0.0002***	0.0001***
	(.0004)	(.000001)	(0.00001)	(0.00001)	(0.00001)
Vehicle type	2.6682***	0.1845***	0.1254***	0.1225***	0.1363***
	(.2380)	(0.0013)	(0.0110)	(0.0109)	(0.0107)
GM	-3.3919***	-0.1461***	-0.0812***	-0.0797***	-0.0896***
	(.2990)	(0.0024)	(0.0135)	(0.0135)	(0.0131)
CHRYSLER	-0.6675*	-0.0562**	-0.0332**	-0.0152	-0.0397**
	(.3706)	(0.0088)	(0.0160)	(0.0163)	(0.0156)
HONDA	-5.4454***	-0.3212***	-0.2066***	-0.2003***	-0.2350***
	(.3693)	(0.0019)	(0.0176)	(0.0168)	(0.0171)
TOYOTA	-3.1039***	-0.1485***	-0.0883***	-0.0830***	-0.0924***
	(.3649)	(0.0042)	(0.0180)	(0.0176)	(0.01755)
NISSAN	-2.9167***	-0.0971***	-0.0414**	-0.0345*	-0.0487**
	(.4413)	(0.0084)	(0.0206)	(0.0208)	(0.0201)
MAZDA	-0.0071	0.0107	0.0141	0.0014	0.0084
	(.6684)	(0.1414)	(0.0281)	(0.0291)	(0.0273)
MITSUBISHI	2.1188***	0.313***	0.2433***	0.2482***	0.2328***
	(.7253)	0.0075	(0.0350)	(0.0327)	(0.0340)

MERCEDES	-7.4882***	-0.6036***	-0.4187***	-0.4334***	-0.4300***
	(1.3840)	(0.0104)	(0.0573)	(0.0619)	(0.0558)
VOLVO	-1.4548	-0.2294*	-0.1849*	-0.2015*	-0.1472
	(2.2268)	(0.083)	(0.0997)	(0.1074)	(0.0970)
VW	0.3711	-0.1845**	-0.1454***	-0.1797***	-0.1352***
	(1.3230)	(0.0293)	(0.0531)	(0.0563)	(0.0517)
ISUZU	0.3570	-0.0134	-0.0181	-0.0229	-0.0003
	(1.0183)	(0.2847)	(0.0446)	(0.0492)	(0.0434)
Other Manufacturers	-4.5482***	-0.4012***	-0.2894***	-0.2897***	-0.2536***
	(1.2294)	(0.01)	(0.0457)	(0.0508)	(0.0444)
JAPAN	-1.5790***	-0.1511	-0.1124***	-0.1189***	-0.1162***
	(.3030)	(0.0027)	(0.0145)	(0.0140)	(0.0141)
CANADA	1.1646***	0.0957***	0.0690***	0.0681***	0.0700***
	(.3234)	(0.0045)	(0.0150)	(0.0141)	(0.0146)
GERMANY	-2.6286**	-0.2514***	-0.1855***	-0.1974***	-0.2187***
	(1.1986)	(0.0176)	(0.0481)	(0.0526)	(0.0468)
MEXICO	0.8245	0.1357***	0.1056***	0.1140***	0.1096***
	(.5315)	(0.0111)	(0.0281)	(0.0264)	(0.0273)
SWEDEN	-2.4005	-0.2258*	-0.1577*	-0.1595	-0.2102**
	(2.0623)	(0.0749)	(0.0940)	(0.1006)	(0.0914)
KOREA	5.3230***	0.3129***	0.2159***	0.2159**	0.1652***
	(1.6513)	(0.0247)	(0.0634)	(0.0705)	(0.0617)
UK	-2.7516*	-0.2502**	-0.1743**	-0.1978**	-0.2807***
	(1.6742)	(0.0409)	(0.0731)	(0.0802)	(0.0711)
Other countries	-0.2035	-0.1039	-0.1048	-0.1803	-0.0362
	(2.4016)	(0.2665)	(0.1202)	(0.1358)	(0.1170)
AIR	-0.3444	-0.0426***	-0.0321***	-0.0287**	-0.0354***
	(.2814)	(0.0063)	(0.0118)	(0.0116)	(0.0115)
TWC	2.4450	0.0157	-0.0175	0.0236	0.0876
	(2.2958)	(0.9812)	(0.0885)	(0.0862)	(0.0861)
EGR	-2.5517***	-0.1648***	-0.1096***	-0.1215***	-0.1118***
	(.2719)	(0.0018)	(0.0124)	(0.0123)	(0.0121)
CLL	-7.0427***	-0.7294***	-0.5101***	-0.4511***	-0.5597***
	(1.6865)	(0.0138)	(0.0724)	(0.0721)	(0.0704)
TAC	1.7389***	0.0527**	0.0241	0.0272	0.0159
	(.5428)	(0.0129)	(0.0188)	(0.0186)	(0.0183)
OXY	3.4930*	0.1373*	0.0778	0.0911	0.1600***
	(1.8421)	(0.0504)	(0.0601)	(0.0583)	(0.0585)
PCV	8.2188***	0.3772***	0.2222**	0.1434**	0.2214**
	(2.4382)	(0.0447)	(0.0938)	(0.0729)	(0.0913)
Ambient temperature (F)	-0.0739***	-0.007***	-0.0051***	-0.0052***	-0.0051***
	(.0072)	(.00002)	(0.0003)	(0.0003)	(0.0003)
Relative humidity (%)	-0.1027***	-0.007***	-0.0048***	-0.0049***	-0.0048***
	(.0053)	(.00001)	(0.0002)	(0.0002)	(0.0002)
Pressure (inches, Hg)	-0.3995	-0.0035	-0.0007	0.0094	0.0102
	(.9251)	(0.8855)	(0.0417)	(0.0407)	(0.0406)
Speed (MPH)	0.2894***	0.0274***	0.0202***	0.0202***	0.0198***
	(.0104)	(.00001)	(0.0004)	(0.0004)	(0.0004)
Acceleration (MPH/sec)	1.6908***	0.1244***	0.0853***	0.0730***	0.0901***
	(.0969)	(0.0003)	(0.0043)	(0.0042)	(0.0042)
Sine (road gradient)	-0.6072***	-0.0616***	-0.0458***	-0.0427***	-0.0434***
	(.1398)	(0.0012)	(0.0062)	(0.0060)	(0.0060)
Adj-R^2	20.07%	NA	23.21%	80.40%	NA
Root MSE	27.501	NA	1.2631	2.4543	NA
F or LR test	264.87	24394.71	380.37	5075.27	421.97

(69, 86518)					
Lambda	1	.1507582	0	0	0

1) Statistics in brackets () are the standard errors of coefficients
2) Coefficient value with one * shows significance at 90% confidence level and 10% probability of type-I error; two ** at 95% confidence level and 5% probability of type I error; and three *** at 99% confidence level and 1% probability of type I error.
3) The Log-linear WLS model is run with no constant parameter. Rather, the weight variable is added as an explanatory variable, whose coefficient is reported in place of the constant.

In table 6.4, the coefficients on time variables show that the vehicles emitted similar NO emissions in 2000 compared to average 1999 levels; but NO emissions decreased by 28.01% in 2001. Given this temporal trend of decreasing NO emission factors from 1999/2000 level to 2001, the *ceteris paribus* effect of cooperative and non-cooperative decision behaviors on NO emission factors is computed by the coefficients on the interactions terms in table 6.4. The chow test rejects the null hypothesis that there is no structural change over time in NO emission factors, which is caused by decisions of vehicle owners in both control and treatment groups.[103]

Of the two apparently cooperative fleets, retest pass fleet vehicles were emitting 35.42% more NO emissions than the control fleet vehicles in 1999. The coefficient is significant in all the five models at a 99% confidence level. The models are in agreement with respect to 2000 and 2001 retest pass fleets; there being no decrease in NO emissions of retest pass vehicles from their 1999 levels. The log-linear WLS model predicts that there was no statistical difference between NO emissions of the migrated pass, retest fail, missing fail and control group vehicles between 1999 and 2001.

The fourth non-cooperative fleet, missing pass vehicles, produced 17.18% higher NO emissions than the control fleet vehicles in 1999. According to the three log-linear models, there was no significant change in NO emissions of missing pass vehicles in 2000 as compared to their difference in 1999. In 2001, however, missing pass vehicles emitted 31.75% less NO emissions than their 1999 level difference of 17.18%. Missing pass vehicles thus emitted higher NO emissions as compared to the control group vehicles in 1999 and 2000, but the difference disappeared in 2001.

---

[103] Formally, the null hypothesis of the chow test states β_q, δ_t, $\Delta_{tq} = 0$, where q = {2,3,…,11} and t={4,5}. The F-test statistic for (32,86518) degrees of freedom is estimated at 40.78 [Prob > F = 0.0000] for the OLS with robust errors model and 48.78 [Prob > F = 0.0000] for the log-linear model in table 6.3. Both OLS with robust errors and log-linear models thus reject the null hypothesis of the chow test.

For NO emission factors, the null hypothesis [H_2] states: The difference between the NO emissions of cooperative and non-cooperative vehicle owners is not significantly different than zero. While it is possible to test this hypothesis for each year of the study, here the results for 3 years of the study period, taken together, are presented. This null hypothesis is tested by employing an F-test after estimating equation 5.5 for each of the five regression models. Here the results from the log-linear with robust errors model are reported. Formally, the null hypothesis is stated as follows:

(6.4) $[\beta_6 + \beta_7 + \Delta_{4,6} + \Delta_{5,6} + \Delta_{4,7} + \Delta_{5,7}]/6 = [\beta_8 + \beta_9 + \beta_{10} + \beta_{11} + \Delta_{4,8} + \Delta_{5,8} + \Delta_{4,9} + \Delta_{5,9} + \Delta_{4,10} + \Delta_{5,10} + \Delta_{4,11} + \Delta_{5,11}]/12$, where 6 and 12 respectively represent the number of parameters for cooperative and non-cooperative vehicle groups in estimated equation 5.5, as presented in table 6.4.

For equation 6.4, the F-test statistic with (1,86518) degrees of freedom is estimated to be 0.07 [Prob > F = 0.7879]. The log-linear model cannot reject the null hypothesis [H_2] of equation 6.4 and predicts that there is no statistical difference between NO emission factors of cooperative and non-cooperative vehicles during the period 1999 to 2001.

6.3.4: Human decision behaviors and CO, HC and NO mass emission rates from 1997 to 2001

The methods to convert mass emission factors (g/g) into mass emission rates (tons per year or tons per day) are presented in detail in appendix A. As explained in appendix A, reduced regression models were used to estimate emission rates for CO, HC and NO as impacted by the decision behaviors of vehicle owners as well as regulatory mechanism designers. Full models, as presented in sections 6.3.1, 6.3.2 and 6.3.3, were not used because fuel economy data for each manufacturer, country of vehicle manufacturing, vehicle type and model year of the vehicles in the study sample is presently not available. Further, as explained in section 5.4.1, the odometer data is either not available or not reliable as reported in the vehicle registration data. For these reasons, aggregate VMT data for the state of Georgia was used; and, in estimating mass emission rates, it was assumed that every vehicle observed in the Atlanta 13 county area travels on average the same distance (in miles) per year. Given these important assumptions, panel A, B and C in table A.3 present estimated CO, HC and NO

mass emission rates respectively for 11 vehicle groups during the five years of the study period.

From a big-picture perspective, CO tail-pipe emission rates from Georgia-registered on-road vehicles, which were observed driving inside the 13-county area, declined from 0.492 million tons per year in 1997 to 0.281 million tons per year in 2001. Similarly HC emission rates declined from 62,660 tons per year in 1997 to 6,170 tons per year in 2001. NO emission rates, on the other hand, increased from 46,600 tons per year in 1999 to 49,034.66 tons per year in 2001. CO and HC emissions are decreasing because fleet turnover rate is relatively high in the Atlanta area and younger/newer vehicles are relatively quickly incorporated in its vehicle fleets. The most disturbing finding concerns the increase in NO emissions, because NO is one of the most important ground-level Ozone pre-cursor criteria pollutants. NO emissions are increasing because of the increased use of trucks/SUVs in Atlanta, GA, as shown in table A.2.

The vehicles in the treatment groups of this study do not appear to be significantly reducing overall emissions, and in some cases, are rather increasing them. It is only the vehicles in the control groups that appear to be reducing CO, HC and NO emission rates. But then, was the IM policy intervention targeted at the vehicles in the control groups? Since cooperative vehicle owners [as explained in chapters 1 and 5] can preemptively repair the emission control systems, and be included in the control [initial test/initial pass] fleet of vehicle owners, it makes sense to analyze CO, HC and NO emission rates for each of the 11 fleet types separately. This will also facilitate the analysis in terms of estimating the effects on vehicular tail-pipe emissions due to changes in IM program rules, such as the shift from a biennial to an annual program in 2001.

The overall effectiveness of IM program in Atlanta between 1997 and 2001 is calculated by considering the change in total emissions from year to year in the vehicle fleet groups that were eligible to appear in the IM program for an evaluation year. Of the 11 fleets considered in detail here, 2 fleets were not eligible, including the IM ineligible fleet and the rest-of-GA fleet. The rest of the 9 fleets were eligible. The total CO, HC and NO emissions produced by IM eligible fleets in each year of evaluation are shown in table A.3. Further, CO, HC and NO emissions produced by cooperative and non-cooperative fleets are also shown for each year in table A.3.

Summary of the IM program's emission-rate reduction effectiveness is as follows, as presented in table A.3: CO emission rates for odd model year IM eligible vehicles observed in 1997 increased by 2.92% in 1999; and, even model year IM eligible vehicles observed in 1998 decreased by 24.01% in 2000. If combined for both odd and even model years observed in 1999 and 2000, CO emission rates decreased by 37.31% in 2001. Similarly, HC emission rates for odd model year IM eligible vehicles observed in 1997 decreased by 35.01% in 1999; and, even model year IM eligible vehicles observed in 1998 decreased by 12.51% in 2000. HC emission rates for both odd and even model year vehicles observed in 1999 and 2000 decreased by 79.12% in 2001. Furthermore, NO emission rates for both odd and even model year vehicles observed in 1999 and 2000 decreased by 11.32% in 2001.

6.4: Contextual conditions of vehicle owners in the Atlanta airshed

The contextual conditions of vehicle owners are estimated through two models. First, a multinomial logistic regression model is employed to test the differences in the socio-economic, demographic and technological contextual conditions of vehicle owners in control and treatment groups of vehicle owners. Section 6.4.1 elaborates the results from this model. Second, an ecological regression model is employed to test the differences in the distribution of median household income of vehicle owners' block-group level neighborhoods. Section 6.4.2 presents the results from this model. The results of the hypotheses H_3 and H_4 are also presented there.

6.4.1: Socio-economic, demographic and technological contextual conditions of vehicle owners in the Atlanta airshed 1997-2001

Table 6.5 presents results from the multinomial logistic regression model that predicts the odds of vehicle owners to be in one of the four control or six treatment vehicle groups as compared to the control (initial test/initial pass) group vehicles. The odds are predicted for 17 parameters on socio-economic and demographic contextual conditions of vehicle owners and 29 parameters on technological characteristics of their vehicles. The model was run on the geo-coded sample of 482,809 vehicle owners observed in Atlanta between 1997 and 2001. The model has a pseudo-R^2 of 55.47%.

The economic context of the vehicle owners in the Atlanta airshed is captured by four economic parameters of vehicle owners, which are measured at the vehicle owners' census block-group levels: median household income, per capita income, median home value and % of employed. As the median household income of the vehicle owner's

Table 6.5: Multinomial logistic regression model predicting the odds of vehicle owners' socio-economic, demographic and technological contextual conditions [N= 482,809; Psuedo R² = 55.47%]

Predictors	Ineligible fleet (Q2)	Waived fleet (Q3)	Rest-of-GA fleet (Q4)	Missing fleet (Q5)	Retest pass (Q6)	Migrated pass (Q7)	Retest fail fleet (Q8)	Migrated fail (Q9)	Missing fail (Q10)	Missing pass (Q11)
Household income ($)	1.00327*** (0.0003)	0.9888*** (0.00028)	0.9290*** (0.0008)	0.9963*** (0.0009)	0.9908*** (0.0011)	0.9531*** (0.0020)	0.9915*** (0.0026)	0.9420*** (0.0064)	0.9773*** (0.0026)	0.9901*** (0.0008)
Per capita income ($)	0.9946*** (0.0008)	1.0306*** (0.0064)	0.9979 (0.0021)	0.9978 (0.0021)	1.0168*** (0.0026)	0.9782*** (0.0050)	1.0140** (0.0063)	0.9790 (0.0165)	1.0340*** (0.0063)	1.0132*** (0.0019)
Median home value ($)	1.0020*** (0.0007)	0.9886* (0.0062)	0.9208*** (0.0021)	1.0005 (0.0020)	0.9888*** (0.0026)	0.9710*** (0.0048)	0.9822*** (0.0062)	0.9409*** (0.0166)	0.9858** (0.0062)	0.9933*** (0.0018)
% Employed	0.9725*** (0.0064)	0.8863*** (0.0403)	0.8937*** (0.0107)	0.9252*** (0.0144)	1.0110 (0.0187)	0.8378** (0.0233)	1.0954* (0.0461)	0.9540 (0.0751)	0.9334* (0.0359)	0.9681** (0.0135)
% Black	1.0047*** (0.0016)	1.0413*** (0.0126)	0.6184*** (0.0021)	0.9807*** (0.0038)	1.0273*** (0.0047)	0.6732*** (0.0056)	1.0319*** (0.0103)	0.6698*** (0.0146)	1.0083 (0.0106)	1.0023 (0.0036)
% Hispanic	1.0399*** (0.0098)	0.8666 (0.0677)	0.7770*** (0.0148)	0.9702 (0.0223)	0.9518* (0.0246)	0.8041*** (0.0361)	0.8950* (0.0515)	0.6609*** (0.0904)	0.9583 (0.0534)	1.0025 (0.0200)
% Asian	0.9475*** (0.0083)	0.9244 (0.0729)	0.2136*** (0.0059)	0.9235*** (0.0205)	1.0265 (0.0264)	0.3618*** (0.0217)	0.9909 (0.0580)	0.4132*** (0.0718)	1.0605 (0.0617)	0.9932 (0.0194)
% Other races	1.0595*** (0.0184)	1.0102 (0.1388)	0.7061*** (0.0242)	0.9630 (0.0412)	1.0190 (0.0474)	0.6970*** (0.0577)	1.1274 (0.1139)	0.7695 (0.1884)	0.9271 (0.0934)	0.8649*** (0.0322)
% female	1.3167*** (0.0132)	0.5591*** (0.0367)	1.2891*** (0.0255)	1.0096 (0.0236)	0.6416*** (0.0171)	0.9667 (0.0403)	0.6071*** (0.0352)	0.7545*** (0.0798)	0.4966*** (0.0283)	0.6660*** (0.0141)
% age 18-24	1.2758*** (0.0135)	0.7590*** (0.0562)	1.0594*** (0.0178)	1.0721*** (0.0253)	0.7177*** (0.0221)	0.8220*** (0.0289)	0.6585*** (0.0457)	0.8201** (0.0640)	0.5467*** (0.0369)	0.7756*** (0.0176)
% age 25-34	1.1916*** (0.0108)	0.8659** (0.0584)	0.6353*** (0.0132)	1.0209 (0.0224)	0.7633*** (0.0201)	0.7522*** (0.0335)	0.7123*** (0.0432)	0.5106*** (0.0681)	0.6124*** (0.0358)	0.8545*** (0.0168)
% age 35-44	1.3484*** (0.0180)	0.6121*** (0.0572)	0.5980*** (0.0161)	1.0169 (0.0321)	0.6216*** (0.0232)	0.4472*** (0.0270)	0.4607*** (0.0389)	0.4231*** (0.0706)	0.4924*** (0.0401)	0.6510*** (0.0187)
% age 45-54	1.2198*** (0.0160)	0.6821*** (0.0670)	1.0727*** (0.0281)	1.0849** (0.0347)	0.7191*** (0.0274)	0.8283*** (0.0503)	0.6248** (0.0537)	0.7252* (0.1231)	0.5713*** (0.0499)	0.7484*** (0.0221)
% age 55-64	1.1475*** (0.0169)	0.9806 (0.1003)	2.9306*** (0.0763)	0.9859 (0.0361)	0.7480*** (0.0330)	1.8563*** (0.1140)	0.8037** (0.0777)	1.4955* (0.2662)	0.5514** (0.0571)	0.7388*** (0.0254)
% age 65 +	1.1386*** (0.0114)	1.1031 (0.0701)	0.7447*** (0.0129)	0.9310*** (0.0229)	0.7688*** (0.0235)	0.6298*** (0.0280)	0.7699*** (0.0524)	0.6049*** (0.0771)	0.5834*** (0.0405)	0.8320*** (0.0192)
Vehicle age (years)	0.4054*** (0.0019)	0.8761** (0.0585)	0.5227*** (0.0039)	0.6651*** (0.0071)	1.2844*** (0.0290)	1.1282*** (0.0245)	1.1674*** (0.0570)	1.2129 (0.1480)	1.1099* (0.0632)	1.1020*** (0.0125)
Vehicle age squared	1.0858*** (0.0006)	1.0601*** (0.0063)	1.0642*** (0.0009)	1.0451*** (0.0011)	1.0114*** (0.0021)	0.9929*** (0.0020)	1.0196*** (0.0047)	1.0303*** (0.0109)	1.0355*** (0.0051)	1.0006 (0.0010)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Vehicle age cubed	0.9980*** (0.00001)	0.9981*** (0.0001)	0.9985*** (0.00002)	0.9989*** (0.00003)	0.9993*** (0.00005)	1.0001** (0.00005)	0.9991*** (0.0001)	0.9987*** (0.0002)	0.9987*** (0.0001)	0.9999*** (0.00002)
Vehicle type	1.1110*** (0.0101)	0.5638*** (0.0439)	1.2368*** (0.0195)	1.0281 (0.0233)	0.9912 (0.0280)	1.0261 (0.0400)	0.7900*** (0.0494)	0.9957 (0.1126)	0.9783 (0.0618)	0.9066*** (0.0192)
GM	1.0528*** (0.0125)	0.9761 (0.0842)	1.1281*** (0.0224)	1.0128 (0.0301)	1.2760*** (0.0462)	1.0265 (0.0480)	1.1380 (0.0927)	1.1784 (0.1652)	1.2784*** (0.1016)	0.9907 (0.0265)
CHRYSLER	1.0313** (0.0154)	1.1924 (0.1459)	1.1174*** (0.0290)	0.9490 (0.0377)	1.4268*** (0.0657)	1.0728 (0.0650)	1.3690*** (0.1421)	0.9379 (0.2043)	1.5655*** (0.1613)	1.0453 (0.0351)
HONDA	0.9991 (0.0158)	0.6062*** (0.0853)	1.1874*** (0.0359)	0.7096*** (0.0311)	1.4260*** (0.0658)	0.9990 (0.0698)	1.1211 (0.1180)	1.6877*** (0.3377)	1.2376* (0.1364)	0.8271*** (0.0301)
TOYOTA	0.9446*** (0.0155)	0.6512*** (0.1069)	1.0108 (0.0320)	0.7825*** (0.0359)	1.1672*** (0.0613)	0.9695 (0.0696)	1.0726 (0.1247)	1.0172 (0.2501)	0.7408** (0.10009)	0.9116** (0.0338)
NISSAN	0.8490*** (0.0151)	0.5055*** (0.0961)	0.9536 (0.0325)	0.8827*** (0.0408)	0.7928*** (0.0492)	0.9274 (0.0718)	0.7491** (0.1033)	0.8858 (0.2334)	0.7251** (0.1054)	0.9599 (0.0384)
MAZDA	0.8937*** (0.0213)	0.5123** (0.1385)	1.0588 (0.0503)	0.7457*** (0.0484)	1.1243 (0.0808)	0.9611 (0.1030)	1.1877 (0.1815)	1.5778 (0.4804)	0.9095 (0.1619)	1.0081 (0.0523)
MITSUBISHI	0.9594 (0.0320)	1.3048 (0.4583)	1.2009*** (0.0751)	1.0597 (0.0919)	1.7071*** (0.1759)	1.1502 (0.1595)	1.8355*** (0.3957)	0.7365 (0.5382)	1.3532 (0.3758)	1.1535** (0.0820)
MERCEDES	1.1324*** (0.0504)	0.2218*** (0.0987)	1.7306*** (0.1775)	0.7736** (0.0950)	0.9783 (0.1193)	0.9139 (0.2362)	0.5280** (0.1598)	0.1460** (0.1209)	0.8793 (0.2446)	0.9184 (0.0935)
VOLVO	0.8083*** (0.0485)	1.2906 (0.7316)	1.0849 (0.1551)	0.6755** (0.1059)	1.3680* (0.2234)	1.1202 (0.4339)	0.9050 (0.2814)	2.0458 (1.6463)	1.2700 (0.5320)	0.9178 (0.1202)
VW	1.1186** (0.0533)	0.6008 (0.2509)	1.1288 (0.1065)	0.9135 (0.1099)	1.5440*** (0.1883)	0.9953 (0.2397)	1.1906 (0.3351)	2.1752* (0.9648)	2.0082*** (0.4872)	1.0592 (0.1139)
ISUZU	0.8226*** (0.0329)	0.8630 (0.3747)	0.8821 (0.0694)	0.9524 (0.0979)	1.4495*** (0.1648)	0.7348 (0.1399)	1.3838 (0.3720)	2.1376* (0.8711)	1.1290 (0.3277)	1.0959 (0.0960)
Other Manufacturers	0.9768 (0.0314)	0.6192* (0.1648)	1.0060 (0.0657)	0.8109*** (0.0623)	1.2357** (0.1036)	1.0062 (0.1640)	1.0949 (0.1959)	1.0840 (0.3774)	1.3310 (0.2381)	1.1442* (0.0808)
JAPAN	1.0643*** (0.0124)	0.7213*** (0.0823)	1.0534* (0.0248)	1.1447*** (0.0335)	1.0791*** (0.0374)	1.0699 (0.0576)	1.1975** (0.0895)	1.2118 (0.1935)	1.2725*** (0.1103)	0.9836 (0.0257)
CANADA	1.0200 (0.0130)	1.0865 (0.1099)	0.9600* (0.0209)	1.0984*** (0.0341)	1.0707* (0.0418)	0.8368*** (0.0469)	1.0484 (0.0922)	0.9589 (0.1671)	0.9731 (0.0908)	0.9957 (0.0293)
GERMANY	1.0431 (0.0340)	0.3089*** (0.0873)	1.0459 (0.0756)	1.0931 (0.0813)	0.8972 (0.0783)	1.0385 (0.1864)	0.8241 (0.1509)	1.1063 (0.4003)	0.6308** (0.1248)	0.7840*** (0.0574)
MEXICO	0.9898 (0.0256)	1.0678 (0.3348)	1.0818*** (0.0474)	1.2023*** (0.0769)	0.9763 (0.1011)	0.9439 (0.1090)	0.9389 (0.2162)	0.5154 (0.3725)	0.9447 (0.2503)	0.9304 (0.0583)
SWEDEN	1.1049** (0.0562)	0.2892** (0.1515)	1.0556 (0.1279)	0.9726 (0.1110)	0.7945 (0.1148)	0.7083 (0.2456)	0.9618 (0.2490)	0.6829 (0.5098)	0.5273* (0.2002)	0.8396 (0.0940)
KOREA	1.0751	1.2256	0.9744	1.6074***	1.2147	0.8723	1.8161**	0.5428	1.3388	1.0627

174

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(0.0480)	(0.5337)	(0.0826)	(0.1530)	(0.1743)	(0.1927)	(0.4698)	(0.5560)	(0.4591)	(0.1042)
UK	0.8692** (0.0551)	1.7E-12 (5.39E-07)	1.1979 (0.1820)	1.1264 (0.2028)	0.8010 (0.1698)	1.9516** (0.5495)	0.4997 (0.3011)	1.1539 (1.2174)	0.5146 (0.2758)	1.0037 (0.1359)
Other countries	1.2202* (0.1337)	1.1967 (0.7396)	1.1736 (0.2513)	1.3628 (0.3759)	0.7041 (0.1983)	0.9892 (0.4682)	1.1084 (0.5859)	1.3026 (1.0241)	0.3464 (0.2540)	1.3060 (0.2450)
AIR	1.2004*** (0.0114)	1.3693*** (0.0996)	1.1103*** (0.0188)	1.1020*** (0.0249)	1.2140*** (0.0322)	1.1762*** (0.0479)	1.1622** (0.0685)	1.5008*** (0.1703)	1.2429*** (0.0748)	1.0264 (0.0223)
TWC	0.0645*** (0.0072)	0.1955*** (0.1092)	0.1204*** (0.0177)	0.2028*** (0.0380)	0.6000* (0.1636)	0.6407 (0.2905)	0.2058*** (0.1045)	0.7095 (0.7335)	0.4195* (0.2112)	0.9325 (0.2155)
EGR	0.9427*** (0.0102)	0.8328 (0.0936)	0.9694 (0.0194)	0.9606 (0.0269)	0.8121*** (0.0275)	1.0368 (0.0511)	0.7536*** (0.0560)	0.6307*** (0.0969)	0.7115*** (0.0578)	0.9635 (0.0237)
CLL	1.2996*** (0.0834)	1.7781 (0.7137)	1.3962*** (0.1429)	0.8098 (0.1137)	0.7839 (0.1471)	1.3716 (0.3925)	1.6481 (0.5977)	1.2200 (0.7975)	1.0551 (0.3872)	0.8165 (0.1225)
TAC	1.0462*** (0.0142)	0.9654 (0.0815)	0.9884 (0.0229)	1.1561*** (0.0340)	1.2149*** (0.0379)	1.0595 (0.0567)	1.4077*** (0.0956)	1.3403** (0.1657)	1.2494*** (0.0961)	1.0423 (0.0302)
OXY	0.0790*** (0.0076)	0.3555*** (0.1423)	0.1719*** (0.0198)	0.2138*** (0.0288)	0.5303*** (0.1093)	0.7833 (0.2935)	0.4009** (0.1504)	0.8839 (0.7195)	0.4673** (0.1662)	0.9542 (0.1770)
PCV	12.7071*** (1.3857)	0.9474 (0.4752)	7936.7*** (1528.8)	6.4046*** (1.1824)	1.3930 (0.3298)	1.6501 (0.7055)	1.2553 (0.5585)	0.4983 (0.4444)	1.1441 (0.4925)	0.4769*** (0.0950)
1998	0.8412*** (0.0271)	1.9594** (0.5313)	1.0641 (0.0702)	0.8158*** (0.0611)	1.1399 (0.0971)	59.03*** (17.98)	1.6140*** (0.2897)	22.31*** (12.31)	8.04*** (2.1958)	20.95*** (2.3299)
1999	0.9193*** (0.0111)	1.9133*** (0.1898)	0.9611* (0.0209)	0.3249*** (0.0092)	1.3800*** (0.0542)	109.6*** (28.76)	1.1471 (0.1019)	34.07*** (15.56)	18.23*** (3.9445)	29.64*** (2.6801)
2000	0.7676*** (0.0091)	1.1039 (0.1167)	0.7418*** (0.0157)	0.2258*** (0.0067)	1.4095*** (0.0540)	84.17*** (22.10)	0.7870*** (0.0731)	30.76*** (14.03)	17.69*** (3.8215)	24.99*** (2.2596)
2001	0.2085*** (0.0026)	1.1540 (0.1251)	0.3741*** (0.0082)	0.1281*** (0.0041)	1.3450*** (0.0517)	45.99*** (12.09)	1.7911*** (0.1460)	15.94*** (7.34)	15.86*** (3.4441)	21.64*** (1.9538)

1) Statistics in brackets ( ) are the standard errors of coefficients

2) Coefficient value with one * shows significance at 90% confidence level and 10% probability of type-I error; two ** at 95% confidence level and 5% probability of type I error, and three *** at 99% confidence level and 1% probability of type I error.

census block-group increased by $ 1,000, the odds of a vehicle owner to be in the ineligible fleet increased by 0.32%, while the odds to be in retest pass, migrated pass, retest fail, migrated fail, missing fail and missing pass fleets decreased respectively by 0.92%, 4.69%, 0.85%, 5.80%, 2.27% and 0.99%. This shows that, overall, vehicle owners in the treatment groups of high-emitting vehicle owners come from relatively low income neighborhoods, while the control groups of normal emitting vehicle owners come from relatively higher median household income neighborhoods.

Similarly, as the median home value of the vehicle owner's census block-group increased by $ 10,000, the odds of a vehicle owner being in the ineligible fleet increased by 0.20%, while the odds to be in retest pass, migrated pass, retest fail, migrated fail, missing fail and missing pass fleets decreased respectively by 1.12%, 2.90%, 1.88%, 5.91%, 1.42%, and 0.77%. This result confirms that the vehicle owners of the control group live in relatively expensive homes than those in the treatment groups.

Surprisingly, as the % of employed people in census block group of vehicle owner's address increased by 10%, the odds of a vehicle being in the ineligible fleet decreased by 2.75%, but the odds of a vehicle being in the retest-fail fleet increased by 9.54%. More expectedly, as the % of employed rose by 10%, the odds of a vehicle being in the retest pass and migrated fail groups were equal, but the odds decreased by 16.22%, 6.66% and 3.19% respectively for a vehicle to be in migrated pass, missing fail and a missing pass fleet.

The social context of the vehicle owners in Atlanta is primarily evaluated by analyzing the racial composition of the vehicle owners' neighborhoods at their census block-group levels. The odds of vehicle owners being in one of the four control or six treatment vehicle groups as compared to the initial test initial pass group vehicles are estimated for five parameters on race. Each of the five parameters represents respectively % of Afro-American, Hispanic, Asian and "other-races" in the census block-groups of vehicle owners, while the % of whites is treated as a reference group.

All the races had equal odds of being in retest pass and retest fail groups, but the odds of Afro-Americans as compared to Whites increased significantly by 2.73% and 3.19%. In migrated fail group, however, the odds are significantly higher to find Whites than Afro-American, Hispanic and Asian races. Afro-Americans are thus blatantly defying the law, as represented by their concentration among the retest fail group of vehicle owners. On the other hand, Whites' concentration in the migrated fail group

shows that they have higher odds to be apparently compliant with the written laws but they are actually non-cooperative.

The demographic context of the vehicle owners in Atlanta is evaluated by analyzing the demographic composition of the vehicle owners' neighborhoods through seven parameters. One of these seven parameters measures % of female as compared to male populations, while the other six parameters compare populations of 18 years and older with 18 years and younger. Populations of 18 years and older are divided in six groups of 10 year intervals.

As the % of female population in the census block-group of vehicle owner's address increase by 10%, the odds of a vehicle being in ineligible fleet increase by 31.67%. On the other hand, in the case of five out of six treatment groups -- retest-pass, retest fail, migrated fail, missing fail and missing pass fleets -- the odds are significantly lower for females than males by 35.84%, 39.29%, 24.55%, 50.34% and 33.40% respectively. The migrated pass fleet has equal odds to contain males and females. Overall, thus, the evidence is strong that vehicle owners living in neighborhoods with higher % of females are more cooperative, while the vehicle owners living in neighborhoods with higher % of males are more non-cooperative.

As the % of the people between the ages of 18 and 24 years increase by 10%, the odds of finding an ineligible fleet vehicle increase by 27.58%, while the odds decrease for finding a retest pass, migrated pass, retest fail, migrated fail, missing fail and missing pass group vehicle by 28.23%, 17.80%, 34.15%, 17.99%, 35.33% and 22.44% respectively. Similarly patterns are observed for the neighborhoods with higher % of the 25- to 34-year old people. On the other hand, the neighborhoods with high % of population between the ages of 55 and 64 years have increased odds by 85.63% and 49.55% to respectively contain migrated pass and migrated fail vehicles. Overall, neighborhoods with higher % of people under the age of 34 years are more cooperative while areas with higher % of 35 year and older people have higher odds to contain non-cooperative vehicle owners.

The technological context of the vehicles can be predicted by parameters measured at various levels of detail and resolution. The multinomial logistic model includes only those technological contextual variables, which both significantly explain the variation in the tail-pipe emissions and provide a measure of meaningful policy discourse. The technological variables include vehicle age, vehicle type, vehicle

manufacturer, country of vehicle manufacture and the specific technology of emission control systems on-board the vehicles. All of these technological parameters significantly explain variation for at least one of the eleven vehicle groups, the dependent variable of the multinomial logistic regression model.

The parameter on vehicle age captures the evolving technological context of vehicles. The multinomial model predicts that as the vehicle age increases by one year, the odds of a vehicle being in the ineligible and the rest-of-GA fleets were 59.46% and 12.39% lower respectively as compared to the control group vehicles. On the other hand, with each additional year of vehicle age, the odds of a vehicle being in one of the treatment groups -- retest pass, migrated pass, retest fail, migrated fail, missing fail and missing pass groups -- increased significantly by 28.44%, 12.82%, 16.74%, 21.29%, 10.99% and 10.20% respectively. This result shows that high-emitting vehicle owners in the treatment vehicle groups own, on average, older vehicles than those of the control or other vehicle groups not directly targeted by the IM policy intervention.

6.4.2: Income distribution of vehicles and their owners

This section presents results about the distribution of median household income of the vehicle owners in four control and six treatment groups of vehicle owners, while holding constant technological contextual parameters of vehicles, as well as other economic, social and demographic contextual parameters of the owners of those vehicles. These results are estimated by applying an ecological regression model, as formally presented in equation 5.10.

Table 6.6 presents three regression models that attempt to estimate equation 5.10. The OLS with robust errors model has an adjusted R^2 of 77.76%, while the log-linear with robust errors model has the adjusted R^2 of 77.56%. The log-linear robust regression model counter-validates the results of the log-linear and the OLS with robust errors models.

According to the OLS with robust errors model, as presented in table 6.6, there is no statistical difference in the block-group level median household income of the vehicle owners who are in the ineligible and waived fleets as compared to the control group vehicle owners. The log-linear model suggests, however, that vehicle owners in the IM ineligible fleet had 0.31% lower income than those in the control group. The household income of the owners of control groups of vehicles, especially initial test/initial pass, waived and ineligible vehicle groups, is thus not statistically different. However, as

178

expected, vehicle owners in the rest-of-GA fleet had $ 8,114.91 [15.14%] lower median household income than those in the control group. Unexpectedly, vehicle owners in the missing fleet had $ 691.39 [1.31%] lower median household income than those in control group, which suggests that vehicles in the missing fleet do not just represent a data matching error, and there may be a systematic undercurrent of avoiding the emissions testing upfront by IM test eligible vehicles.

Table 6.6: Regression models predicting the geo-coded vehicle owners' median household income at 2000 census block-group level measured in US dollars

Predictors	OLS with robust errors model (N= 482,809)	Log-Linear with robust errors model (N= 482,696)	Log-Linear robust regression model (N= 482,809)
Constant	55637.79***	10.28***	10.26***
	(866.18)	(0.0127)	(0.0075)
In-eligible fleet	-23.27	-0.0031***	-0.0033***
	(42.79)	(0.0006)	(0.0005)
Waived fleet	-62.06	-0.0087	-0.0051
	(337.39)	(0.0068)	(0.0047)
Rest-of-Georgia	-8114.91***	-0.1514***	-0.1287***
	(68.34)	(0.0013)	(0.0009)
Missing fleet	-691.39***	-0.0131***	-0.0098***
	(109.15)	(0.0018)	(0.0014)
Retest pass	-387.32***	-0.0040**	-0.0038**
	(117.85)	(0.0020)	(0.0017)
Migrated pass	-6158.16***	-0.1082***	-0.0934***
	(155.70)	(0.0030)	(0.0024)
Retest fail	-254.34	-0.0045	-0.0047
	(255.53)	(0.0046)	(0.0038)
Migrated fail	-6448.11***	-0.1285***	-0.1111***
	(414.18)	(0.0089)	(0.0070)
Missing fail	-1371.85***	-0.0271***	-0.0186***
	(264.80)	(0.0050)	(0.0039)
Missing pass	-601.18***	-0.0099***	-0.0072***
	(96.28)	(0.0016)	(0.0013)
Vehicle age (years)	-135.87***	-0.0022***	-0.0015***
	(5.59)	(0.00009)	(0.00007)
Vehicle type	-9.43	0.0018***	0.0017***
	(42.25)	(0.0007)	(0.0005)
GM	-99.78*	-0.0004	-0.0014**
	(53.20)	(0.0009)	(0.0007)
CHRYSLER	600.49***	0.0116***	0.0057***
	(70.53)	(0.0011)	(0.0009)
HONDA	925.16***	0.0199***	0.0142***
	(75.90)	(0.0012)	(0.0010)
TOYOTA	871.50***	0.0159***	0.0102***
	(78.51)	(0.0012)	(0.0010)
NISSAN	670.86***	0.0131***	0.0099***
	(84.67)	(0.0013)	(0.0011)

MAZDA	448.38***	0.0102***	0.0079***
	(114.01)	(0.0018)	(0.0015)
MITSUBISHI	-445.09***	-0.0024	0.0002
	(153.02)	(0.0026)	(0.0021)
MERCEDES	1461.64***	0.0176***	0.0055**
	(292.75)	(0.0038)	(0.0028)
VOLVO	763.44*	0.0146***	0.0084**
	(392.06)	(0.0053)	(0.0039)
VW	6.83	0.0061	0.0054*
	(243.36)	(0.0038)	(0.0029)
ISUZU	321.90*	0.0084***	0.0038
	(187.19)	(0.0031)	(0.0026)
Other Manufacturers	869.29***	0.0098***	0.0028
	(180.06)	(0.0026)	(0.0020)
JAPAN	828.75***	0.0131***	0.0066***
	(57.99)	(0.0009)	(0.0007)
CANADA	-400.67***	-0.0074***	-0.0031***
	(56.81)	(0.0010)	(0.0008)
GERMANY	2144.57***	0.0328***	0.0181***
	(194.79)	(0.0027)	(0.0020)
MEXICO	-108.79	-0.0030	-0.0049***
	(122.81)	(0.0019)	(0.0015)
SWEDEN	1807.61***	0.0270***	0.0129***
	(331.05)	(0.0045)	(0.0033)
KOREA	-1663.74***	-0.0272***	-0.0247***
	(207.74)	(0.0038)	(0.0028)
UK	2341.21***	0.0204***	0.0052
	(497.46)	(0.0062)	(0.0041)
Other countries	1291.69**	0.0115	-0.0003
	(529.84)	(0.0085)	(0.0070)
AIR	-118.67***	-0.0025***	-0.0015**
	(45.76)	(0.0007)	(0.0006)
TWC	475.59	0.0066	0.0066
	(350.47)	(0.0060)	(0.0047)
EGR	213.92***	0.0042***	0.0024***
	(53.69)	(0.0008)	(0.0006)
CLL	-48.48	0.0066	0.0032
	(277.51)	(0.0045)	(0.0037)
TAC	-387.57***	-0.0076***	-0.0057***
	(62.12)	(0.0010)	(0.0008)
OXY	459.85*	0.0101**	0.0046
	(240.84)	(0.0045)	(0.0033)
PCV	166.23	-0.0116*	-0.0121**
	(401.82)	(0.0066)	(0.0053)
% Employed	3864.97***	0.1533***	0.1356***
	(39.49)	(0.0009)	(0.0004)
Median home value ($)	1287.38***	0.0144***	0.0209***
	(6.08)	(0.00006)	(0.00002)
% Black	-1284.07***	-0.0238***	-0.0182***
	(9.19)	(0.0001)	(0.0001)
% Hispanic	51.29	-0.0048***	0.0085***
	(49.37)	(0.0008)	(0.0006)
% Asian	3885.31***	0.0584***	0.0497***
	(46.17)	(0.0007)	(0.0005)
% Other races	-1639.93***	-0.0106***	-0.0300***

	(95.46)	(0.0015)	(0.0011)
% female	-2636.78***	-0.0672***	-0.0284***
	(93.65)	(0.0016)	(0.0007)
% age 18-24	-7702.54***	-0.1497***	-0.1646***
	(84.79)	(0.0015)	(0.0006)
% age 25-34	-12018.04***	-0.1662***	-0.1721***
	(54.21)	(0.0009)	(0.0005)
% age 35-44	527.56***	0.0343***	0.0109***
	(104.16)	(0.0017)	(0.0009)
% age 45-54	5085.88***	0.1047***	0.0658***
	(91.01)	(0.0013)	(0.0008)
% age 55-64	-1464.91***	0.0101***	0.0020**
	(113.08)	(0.0016)	(0.0009)
% age 65 +	-7144.83***	-0.0390***	-0.0775***
	(81.38)	(0.0014)	(0.0005)
1998	-552.03***	-0.0027	0.0022
	(182.26)	(0.0027)	(0.0020)
1999	419.15***	0.0048***	0.0055***
	(58.58)	(0.0009)	(0.0007)
2000	52.32	-.000002	-.0000007
	(56.50)	(0.0009)	(0.0007)
2001	432.60***	0.0061***	0.0071***
	(60.48)	(0.0009)	(0.0008)
Adj-R^2	77.76%	77.56%	NA
Root MSE	12,118	0.1985	NA
F or LR test for model fit (58,482750)	18,811.12	20,429.58	49,802.24
Lambda	1	0	0

1) Statistics in brackets () are the standard errors of coefficients
2) Coefficient value with one * shows significance at 90% confidence level and 10% probability of type-I error; two ** at 95% confidence level and 5% probability of type I error; and three *** at 99% confidence level and 1% probability of type I error.

Of the two cooperative fleets in six treatment vehicle groups, vehicle owners in the retest pass fleet had $ 387.32 [0.40%] lower median household income than those in the control group. The second cooperative fleet, migrated pass vehicle owners had $6,158.16 [10.82%] lower median household income than control group vehicle owners.

Surprisingly, vehicle owners in the retest fail fleet, one of the major non-cooperative vehicle groups, showed no statistically significant difference in their median household income compared with those of control group vehicle owners. The lowest of all were migrated fail vehicle owners, who averaged $ 6,448.11 [12.85%] less than the control group vehicle owners.[104] As expected, vehicle owners in the missing fail and

_____

[104] It is unclear whether migrated pass and migrated fail vehicle owners actually come from lower income areas because their geocoded addresses, as reported in vehicle registration databases, represent a time after they had undertaken [pseudo] migration. Their addresses from the IM program data are not available.

missing pass fleets had respectively $ 1371.85 [2.71%] and $ 601.18 [0.99%] lower median household income than those in the control group.

As presented in section 1.3, the third null hypothesis [H_3] of the study states: The odds are equal that high-emitting vehicle owners live in the same income level neighborhoods as do the normal emitters. This null hypothesis is tested by employing an F-test after estimating equation 5.10 for each of the three regression models. Here the results from OLS and log-linear with robust errors models are reported. Formally, the null hypothesis is stated as follows:

(6.5) $[\beta_6 + \beta_7 + \beta_8 + \beta_9 + \beta_{10} + \beta_{11}]/6 = 0$ where 6 represents the number of parameters for treatment vehicle groups in estimated equation 5.10.

For equation 6.5, the F-test statistic with (1,482750) degrees of freedom is estimated to be 594.97 [Prob > F = 0.000] for the OLS with robust errors model and 525.36 [Prob > F = 0.0000] for the log-linear with robust errors model. Both the OLS and the log-linear with robust errors models strongly reject the null hypothesis of equation 6.5. The OLS models predict that there is a statistical difference between the median household income of the vehicles in the six treatment groups as compared to the vehicles in the control group. In order to estimate the direction and magnitude of the difference between the median household income of the treatment and control groups of vehicles, the alternative hypothesis that treatment group vehicle owners live in lower household income neighborhoods as compared to the control group vehicle owners by a difference of d dollars was tested. Formally,

(6.6) $[\beta_6 + \beta_7 + \beta_8 + \beta_9 + \beta_{10} + \beta_{11}]/6 = d$

While the alternative hypothesis presented in equation 6.6 was rejected by the OLS with robust errors model for the values of d between 0 and –2,333, it was not able to reject the alternative hypothesis for the value of d at –2,334 and below at 95% confidence level. It can therefore be concluded that the treatment group vehicle owners, on average, reside in neighborhoods that have $2,334 lower household income as compared to the vehicle owners in the control group. Similarly, the log-linear model predicted that treatment group vehicle owners live in neighborhoods with at least 4.4% lower household income than the control group vehicle owners. Since IM policy intervention is explicitly targeted at the high-emitting vehicle owners in the six treatment groups, it can be concluded that IM policy is unfair because it targets the treatment

group vehicle owners, who live in relatively lower income neighborhoods, and requires them to pay the costs of repairing emission control systems on their vehicles.

The fourth null hypothesis [H_4] of the study states: The odds are equal that cooperative high-emitting vehicle owners live in the same income level neighborhoods as do the non-cooperative high-emitting vehicle owners. This null hypothesis is tested by employing an F-test after estimating equation 5.10 for each of the three regression models. Here the results from OLS and log-linear with robust errors models are reported. Formally, the null hypothesis is stated as follows:

(6.7) $[\beta_6 + \beta_7]/2 = [\beta_8 + \beta_9 + \beta_{10} + \beta_{11}]/4$ where 2 and 4 respectively represent the number of parameters for cooperative and non-cooperative vehicle groups in the estimated equation 5.10.

For equation 6.7, the F-test statistic with (1,482750) degrees of freedom is estimated to be 43.26 [Prob > F = 0.000] for the OLS with robust errors model and 17.36 [Prob > F = 0.0000] for the log-linear model. Both the OLS and the log-linear with robust errors models reject the null hypothesis of equation 6.7. These models predict that there is a statistical difference between the median household income of the vehicle owners in the cooperative groups as compared to the non-cooperative vehicle groups. In order to estimate the direction and magnitude of the difference between the median household income of the cooperative and non-cooperative groups of vehicles, the alternative hypothesis that cooperative group vehicle owners live in higher household income neighborhoods as compared to the non-cooperative group vehicle owners by a factor of [1+k]% was tested. Formally,

(6.8) $[\beta_6 + \beta_7]/2 = [1+k]^*[\beta_8 + \beta_9 + \beta_{10} + \beta_{11}]/4$

While the alternative hypothesis presented in equation 6.8 was rejected by the OLS with robust errors model for the values of k between 0 and 0.32, it was not able to reject the alternative hypothesis for the value of k at 0.33 and above at 95% confidence level. It can therefore be concluded that the cooperative group vehicle owners, on average, reside in neighborhoods that have 33% higher household income as compared to the vehicle owners in the non-cooperative groups. Similarly, the log-linear model predicts that the cooperative vehicle owners live in neighborhoods with 15% higher household income as compared to the non-cooperative group of vehicle owners. The results of H_4 thus suggest that decision-makers living in higher income areas are

expected to be more cooperative with the environmental regulations as compared to the decision-makers in lower income areas.

Next, the implications of the results are presented in chapter 7.

CHAPTER 7

ANALYSIS AND IMPLICATIONS OF THE RESULTS

7.1 Substantive environmental policy implications

7.1.1 Normative analysis of Atlanta's IM program

Despite increase in vehicle miles traveled between 1997 and 2001, the data has shown that CO and HC vehicular tailpipe emissions are decreasing over time, but NO emissions are increasing. The decrease in CO and HC vehicular tailpipe emissions can be partially attributed to IM program effectiveness (as discussed in section 6.3), but changes in gasoline mixes and faster fleet turnovers (parameter vehicle age) are also partially responsible for decrease in CO and HC emissions. On the other hand, the increase in NO emissions is a disturbing finding and immediate policy action is required to change this trend. A strong reason for the increase in NO emissions is attributed to rising stocks of Trucks/SUVs in the Atlanta area. Secondly, the lack of control over high-emitting vehicle owners is also a significant factor in the increased production of NO tail-pipe emissions.

Even though the IM program can identify most of the high-emitting vehicle owners, it is not as effective in reducing emissions from their vehicles as might be achieved by an alternative design of the IM program. The data results show that the emission factors of high-emitting vehicles have either stayed at the same levels or even increased; they did not decrease as was originally mandated under the objective of the IM regulatory mechanism.

The *descriptive level* analysis of the IM program in the Atlanta area shows that if outcomes of policy intervention are measured on the value/objective of tailpipe emission reductions, we get mixed results. On the one hand, the IM program has effectively reduced CO and HC emission by 37.31% and 79.12% respectively from 1999-2000 levels to 2001. On the other hand, at least 58% of high-emitting vehicle owners have

been able to defy the IM program, and their vehicles, on an individual basis, continue to emit about 3 times higher emissions than the control group vehicles.

If outcomes of the IM program intervention are also measured on the scale of fairness, the data shows that the IM program is targeting vehicle owners who live in areas with relatively less median household income than those who are not targeted by it. On the other hand, the benefit of clean air, if effectively produced by IM program intervention, will be shared by both high-emitting and the normal-emitting vehicle owners in the Atlanta airshed. The policy intervention aimed at attaining a positive outcome for the entire society, cleaner air by maintaining high emitting vehicles, results in unfair allocation of environmental clean-up costs: it is unfair because the IM intervention by its design aims at detecting and repairing high-emitting vehicles, which are owned by people with lower median household income levels than the owners of vehicles that are not targeted by the IM program. Is it possible to design a policy mechanism that is both fair and more effective?

If fairness is accepted as a worthy objective by the policy designers, it is perhaps possible that the IM program could be made more effective in reducing tailpipe emissions.[105] But how could it happen? How can we get from here –a less effective and less fair predicament – to there – a more effective and fairer future?

Next, three possible policy options based on three theoretical frameworks are briefly outlined: the first option is based on the assumption that the current theory of environmental regulation will continue to prevail; the second option is based on the assumption that game theoretical predictions hold; and the third option is based on the assumption that collaborative and communicative theories of policy and planning hold. From a meta-theoretical perspective, these three theories and their relevant policy options are not contradictory; they can be pursued simultaneously.

First, given the current theory and practice of environmental regulation, it is important that coordination among various state authorities, statutes and laws be improved, and that the enforcement of the existing laws be increased. While the IM program rules rely on the strategy of regulatory punishment by denying vehicle

---

[105] The hypotheses H_3 and H_4 were written with the intention of treating "fairness" as a "stand-alone" value, an objective worthy of pursuit in itself due to its intrinsic value in human societies. However, the results of the empirical study show that the pursuit of fairness can also affect changes in effectiveness, the other criterion of evaluation in Atlanta's case study.

registration inside the 13 county-area to the program avoiders and non-cooperative vehicle owners, there are both enforcement failures[106] as well as loopholes in the vehicle registration laws, which allow high-emitters to avoid the IM program punishment strategy. Vehicles belonging to the retest fail fleet are unresolved failures but are still found being driven and registered inside the 13 county IM program boundaries. Similarly, missing fail and missing pass group vehicles should appear for emissions testing, but they continue to avoid the IM program regulations. Furthermore, vehicles belonging to the migrated fail category are perfect examples of avoiding the regulatory punishment strategy through perfectly legal means due to the current loopholes in the vehicle registration laws.

If policy-makers and legislators want to decrease the non-cooperative and program avoidance behavior in the Atlanta Airshed and improve the enforcement of IM program regulations, the following two changes in the vehicle registration laws and IM program rules will be required. First, a vehicle that fails an initial IM test inside the 13-county area should not be allowed to register anywhere in the state of Georgia. This change would reduce the percentage of migrated fail vehicles from the on-road fleets in the Atlanta airshed. Possibly, there will be opposition to the proposed change of vehicle registration law from the counties outside the IM program boundary area because it is in their revenue interest to maximize the number of vehicle registrations in their counties. Car dealers are another influential lobby that is likely to oppose the change in the vehicle registration laws. It is not in their interest to increase governmental intervention in the transaction processes associated with vehicle registrations. On the other hand, this study provides substantial evidence that migrated fail vehicles are producing tailpipe CO, HC and NO emissions at least 3 times higher than the control group vehicles. The proposed change in the vehicle registration laws will thus improve the air quality in the Atlanta airshed by reducing the percentage of the migrated fail vehicles from on-road fleets.

Secondly, the missing fail and missing pass groups of non-cooperative vehicles can be reduced by introducing a change in the current IM program rules. The new rule would require a vehicle inside the 13-county area to undergo emissions testing at every

---

[106] Vehicles in retest fail, missing fail and missing pass groups represent enforcement failures, while migrated fail vehicles represent the vehicle owners who exploit loopholes in the vehicle registration laws.

change of ownership. This rule will both improve the air quality and provide more up-to-date information to IM program managers about the history of vehicles in the IM program area, especially the tracking of high-emitting vehicle owners would become much easier task. Furthermore, a follow-up evaluation study in the future would be able to distinguish the actual non-cooperative types in the missing pass group from those new vehicle owners who are not required by the IM program rules to test the vehicle for emissions' compliance.

A game theorist might argue, it is not certain that the proposed changes in the vehicle registration laws and IM program rules will be sufficient to ensure compliance by high-emitting vehicle owners. For example, if the vehicle registration law is modified to disallow an IM failure from getting registered anywhere in the state of Georgia, the non-cooperative drivers can still register outside the state of Georgia (say in Tennessee) and still drive in the Atlanta Airshed. This implies that a concerted and coordinated action at the regional or national level will be required to completely stop the program avoidance behavior.

Game theory suggests that the current incentive structure for the high-emitting vehicle owners induces program avoidance behavior, because it is less costly to register a car outside the IM program boundaries than taking it again and again to the IM testing stations. Instead, a clean air fund could be initiated through a very small tax on normal emitting vehicle owners [because they would enjoy the benefit of clean air] and repair subsidies can be issued to the high-emitting vehicle owners that show reliable receipts for repairing the emission control systems on their vehicles from the state-certified repair centers. Other forms of rebates can also be considered to induce a change in the behavior of non-cooperative high-emitting vehicle owners, such as incentives to vehicle manufacturers to issue subsidized warrantees of up to 200,000 miles on emission control systems for the vehicles produced by them. Thus, a change in the incentive structures through a detailed mechanism design may induce non-cooperative drivers to start cooperating with the environmental laws.

A qualitative study should directly elicit the cognitive perspective of the non-cooperative vehicle owners. This study may involve intensive focus groups involving representatives of high-emitting vehicle owners from various socio-economic backgrounds to discuss new policy alternatives for encouraging cooperative behavior and improving air quality in the Atlanta Airshed. This suggestion is based on the

assumption that discussion and negotiation with actual people may bring a new set of policy alternatives to the forefront, and allow progress beyond the current policy of regulatory punishment through the vehicle registration laws and the proposed policy of changes in incentive structures through repair-subsidies and manufacturer warranties.

To put it simply, a normative underpinning for the policy intervention would be required. It will have to be recognized by the policy makers that fairness is an important value against which the outcomes of policy interventions should be measured. Whether fairness is recognized as an important value by the policy-makers/designer is an example of a meta-decision problem. At the same time, a contextual change in vehicular technologies and fuel-inputs might perhaps one day eradicate the need for an IM program. In the short to medium run (at least for the vehicles up to model year 2007), it seems that a mechanism will be required to efficiently maintain constantly aging vehicles in the current fleets.

Some form of policy intervention will therefore be needed to detect and repair the high-emitting vehicle owners in the Atlanta fleet during the next twenty-five years (assuming 2007 model years would be scrapped around 2029). It is in the purview of the policy makers to change the regulatory mechanism and make it more fair and effective. This change can be brought about by changing the current vehicle registration laws and IM program rules, re-designing the incentive structures for high-emitting vehicle owners and carrying out direct discourse with the representatives of high-emitting vehicle owners. Adaptive mechanisms, discussed in next section, present a formal method to bring about changes in policies that aim at balancing outcomes of policy interventions on multiple scales of values in a context-sensitive design.

7.1.2 Designing adaptive environmental policy mechanisms: revisiting voluntary, regulatory and market mechanisms

Consider the framework of a multi-stage principal-agent (*P-A*) decision game for comparing the outcomes of voluntary, regulatory and market mechanism designs with one another as well as designing adaptive policy mechanisms. The *P-A* framework allows evaluation of current incentive mechanisms faced by the environmentally regulated. It also facilitates the design of alternative mechanisms for aiding the decisions of environmental regulators/policy makers. The *P-A* game thus provides a theoretical framework to model the incentive mechanisms for both *ex post* evaluation of previous environmental policies and *ex ante* design of alternative incentive mechanisms.

The environmental regulator is modeled as Principal, which sets the rules of the game in period *t*. Agents react to these rules in period *t + 1*. Some agent *types* follow the rules of the game by pursuing cooperative strategies that enable the environmental regulator to meet environmental standards as envisioned in the enforced regulations. Other agent *types* try to avoid or circumvent the rules of the game by pursuing non-cooperative strategies that enable them to free-ride in consuming environmental goods as well as to avoid the regulatory punishment strategy that is enforced by the Principal for maximizing the prevalence of cooperative strategies. In period *t + 2*, the environmental regulator evaluates the implementation of the regulatory standards and either continues to implement the previous rules or changes the rules of the game, to which agents react in period *t + 3*. The multi-stage principal-agent game continues until there is no need for environmental regulation.

Formally, a mechanism is defined as an institution with rules governing the procedure for making a collective choice. The environmental regulatory mechanism is denoted as τ_R, while the adaptive mechanism is denoted as τ_A. A voluntary mechanism is denoted as τ_V, and a market mechanism is denoted as τ_M. In real-world practice, it would be very difficult to sharply segregate voluntary, market and regulatory mechanisms from each other. A voluntary mechanism may operate side by side with a market; or a regulatory mechanism may intervene in a market mechanism; or a regulatory mechanism may leave voluntary choices to the decision-makers. An adaptive mechanism does not need to introduce sharp boundaries between voluntary, regulatory and market mechanisms; rather it can be initiated under any existing circumstances, as described in section 2.4.

Suppose there are *m* agents in the game, denoted by set *M = 1,…, i,…,m*; while Principal is the *m+1*[st] player. The *m* agents must make a collective choice from the set *X* (for example, clean air or no clean air). The collective choice is, however, assumed to be realized by each agent's individual strategy and *type*. Each agent's strategy set is denoted by S_i, and there are $(S_1,…,S_m)$ sets of strategies played by *m* agents in the game.

The *P-A* game is modeled as a game with incomplete information (Harsanyi 1995) because each player's strategy and payoff will depend on which particular type of

her represents her in the game. In other words, the P-A game allows multiple *types* of a player to play in different time periods, even though only one type of player plays at a single moment of time. For each player *i* in *M*, let the number of her different types be *z (i)*. The set of all her types is denoted as:

$$\Theta_I = (\vartheta^i_1, \vartheta^i_2, \ldots, \vartheta^i_g, \ldots, \vartheta^i_z).$$

The total number of different types in the game will be:

$$Z = \sum^m_{i=1} z\ (i).$$

For any type ϑ_i, the number of her pure strategies is called *K (i)*. The set of all her pure strategies is written as $S_i = (s^1_i, \ldots, s^k_i, \ldots, s^{K(i)}_i)$. Since ϑ_i is observed only by agent *i*, the game setting is characterized by incomplete information. It is assumed that agents' types are drawn from a commonly known prior distribution. Denoting a profile of agents' types by $\vartheta = (\vartheta_1, \ldots, \vartheta_m)$, the probability density over the possible realizations of all profiles of agents' types $[\vartheta \in \Theta_1 \times \ldots \times \Theta_m]$ is represented as $\phi(.)$. The probability density $\phi(.)$, the sets $\Theta_1 \times \ldots \times \Theta_m$ and the utility functions $u_i (x, \vartheta_i)$ are assumed to be individual beliefs of the agents and specific value of each agent *i*'s type is observed only by *i*.[107]

Each agent *i* is assumed to be an expected utility maximizer.[108] The Bernoulli utility function of type ϑ_i is $u_i (x, \vartheta_i)$. The ordinal preference relation over pairs of alternatives in *X* that is associated with utility function $u_i (x, \vartheta_i)$ is denoted $\geq_i (\vartheta_i)$. Agent *i*'s set of possible preference relations over *X* is given by:

$$R_i = \{\geq_i : \geq_i = \geq_i (\vartheta_i)\ for\ some\ \vartheta_i \in \Theta_i\}.$$

Definition 1: A social choice function is a function $f : \Theta_1 \times \ldots \times \Theta_m \_ X$ that, for each possible profile of the agents' types $(\vartheta_1, \ldots, \vartheta_m)$, assigns a collective choice f $(\vartheta_1, \ldots, \vartheta_m)$ $\in X$.

---

[107] It is possible that agent *i*'s type is observed by agent *j* and thus agents' preferences over outcomes depend not only on their own observed types but also on types observed by others (e.g. agent *i*'s preferences over whether or not to cooperate with the environmental regulations may depend on agent *j*'s knowledge of possible strategies). Though it is possible to model the influence of other people's knowledge on an agent's actions and strategies, this dissertation is restricted to the case in which each individual acts according to his/her own knowledge and type (also known as the case of *private values*).
[108] As discussed in chapter 3, other forms of utility functions under uncertain states of the world can also be assumed, or interactively constructed for specific decision makers.

Definition 2: The social choice function $f : \Theta_1 \; x \; \ldots \; x \; \Theta_m \; \_ \; X$ is *ex post efficient* (or *Paretian*) if for no profile $\vartheta = (\vartheta_1, \ldots, \vartheta_m)$ is there an $x \in X$ such that $u_i \, (x, \, \vartheta_i) \geq u_i \, (\, f \, (\vartheta), \vartheta_i)$ for every *i*, and $u_i \, (x, \, \vartheta_i) > u_i \, (\, f \, (\vartheta), \vartheta_i)$ for some *i*.

The social planner (Principal) faces the problem that ϑ_i's are not publicly observable, and it is not known which type of an agent is playing the game. It is therefore very difficult to decide which social choice function (or incentive mechanism design) should be chosen or preferred as efficient. One way to elicit the agent types of ϑ_i's is to use direct revelation mechanisms. Free riders, or non-cooperative types, will however have the incentive not to truthfully tell their type under the direct revelation mechanism designs. Let's suppose that there are two kinds of strategies played by agents: cooperative strategies are denoted by S_c and non-cooperative strategies are denoted by S_{nc}. If an agent pursues a cooperative strategy, it is inferred that her cooperative type is active in the game and her other types are inactive. The possibility of preference reversal is not excluded: if Principal changes the incentive mechanism from τ_R to τ_A, it is possible that the type of agent pursuing non-cooperative strategies may find cooperative strategies to be of higher expected utility and reverse her preferences by changing her active type in the game.

Once the active agent types are measured through an indirect methodology, the next task of the social planner is to design a mechanism such that agents will play the equilibrium strategies and yet implement the Pareto efficient social function. This task could be modeled in two steps. First, a currently enforced mechanism under the given environmental regulation τ_R is estimated to ascertain the existing social choice function, which is also known as the outcome function in game-theoretical language and formally represented as $g: S_1 \; x \; \ldots x \; S_m \; \_ \; X$. In the second step of policy prescription, an alternative mechanism τ_A is proposed that will change the incentive structures and the equilibrium strategies of agents given both their types observed in the previous stages of the game and the desirable values enshrined in measuring the outcomes of agents' actions. The change in the incentive structure and strategies of agents will lead to an altered social choice or outcome function that would be realized in period t +1, and so on. Formally, a mechanism is defined as follows:

Definition 3: A mechanism $\tau = (S_1,\ldots, S_m, g(.))$ is a collection of m strategy sets $(S_1,\ldots, S_m)$ and an outcome function $g: S_1 \times \ldots \times S_m \_ X$.

The observed actions of each agent type in the study sample are summarized by the strategy set S_i, and the rule for how agents' actions get turned into a social choice function is given by the outcome vector-valued function $g(.)$. Moreover, the mechanism τ combined with possible agent types $(\Theta_1 \times \ldots \times \Theta_m)$, probability density $\phi(.)$ and Bernoulli utility functions $(u_1(.), \ldots, u_m(.))$ defines a Bayesian game of incomplete information. Assuming $(u_{-i}(s_1, \ldots, s_m, \ ), \vartheta_i) = u_i(g(s_1, \ldots, s_m, \ ), \vartheta_i)$, the Bayesian game is defined to contain the following elements: $[M, \{S_i\}, \{u_{-i}(.),(\Theta_1 \times \ldots \times \Theta_m), \phi(.)]$

The Bayesian game of incomplete information generated by a mechanism τ shows that a strategy for agent i is a function $s_i: \Theta_i \_ S_i$, which depicts agent i's choice from S_i for each possible type in Θ_i. In other words, a mechanism implements social choice function $f(.)$ if there is an equilibrium of the game induced by the mechanism that yields the same outcomes as $f(.)$ for each possible profile of types $\vartheta = (\vartheta_1,\ldots, \vartheta_m)$. The formal definition is as follows:

Definition 4: The mechanism $\tau = (S_1,\ldots, S_m, g(.))$ implements the social choice function $f(.)$ if there is an equilibrium strategy profile $(s_1^*(.), \ldots, s_m^*(.))$ of the game induced by τ such that $g(s_1^*(\vartheta_1), \ldots, s_m^*(\vartheta_m)) = f(\vartheta_1,\ldots, \vartheta_m)$ for all $(\vartheta_1,\ldots, \vartheta_m) \in \Theta_1 \times \ldots \times \Theta_m$.

One of the most persistent and most discussed problems in decision theory concerns the choice of which decision rule should be chosen to define a social choice function $f(.)$, because there is no universally agreed upon meta-criteria to identify and weight the parameters of a social choice function. Different parameters and their weights may lead to different equilibriums in a P-A game.

Let's suppose that the social planner decides on a dictatorial basis to implement a social choice function that, for example, in the context of this study, minimizes emissions per gallon of burned gasoline fuel and fairly distributes the repair costs for the drivers of the Atlanta airshed. In this case, a multi-criteria social choice function or outcome function has been reduced by the dictator to a bi-criteria social choice function. Effectiveness represents one criterion which is measured as minimum emissions per

gallon; and fairness represents the second criterion which is measured as a uniform distribution of repair costs over all income levels of the agents in this game.

The question remains: which equilibrium concept should be employed to solve the decision game.[109] Current research in game theory has come up with multiple solutions (Fudenberg and Tirole 1991). Two of the most commonly employed concepts are dominant strategy equilibrium, and Bayesian Nash equilibrium.

A strategy is a weakly dominant strategy for an agent in a game if it gives her at least as large a payoff as any of her other possible strategies for every possible strategy that other agents might play. In an incomplete information setting, strategy $s_i: \Theta_i \_ S_i$ is a weakly dominant strategy for agent i in mechanism $\tau = (S_1,\ldots, S_m, g (.))$ if, for all $\vartheta_i \in \Theta_i$ and all possible strategies for agents $j \neq i$, $s_{-i} = [s_1 (.), \ldots, s_{i-1} (.), s_{i+1} (.), \ldots, s_m (.)]$:

$$E_{\vartheta_{-i}} [u_i (g (s_i (\vartheta_i), s_{-i} (\vartheta_{-i})), \vartheta_i) / \vartheta_i] \geq E_{\vartheta_{-i}} [u_i (g (s_i\hat{}, s_{-i} (\vartheta_{-i})), \vartheta_i) / \vartheta_i] \text{ for all } s_i\hat{} \in S_i.$$

Where $E_{\vartheta_{-i}}$ represents the expectation taken over realizations of $\vartheta_{-i} \in \Theta_{-i}$. The above condition leads to the following formal definition of the dominant strategy equilibrium:

Definition 5: The strategy profile $(s_1^* (.), \ldots, s_m^* (.))$ is a dominant strategy equilibrium of mechanism $\tau = (S_1,\ldots, S_m, g (.))$ if, for all i and all $\vartheta_i \in \Theta_i$,

$$u_i (g (s_i^* (\vartheta_i), s_{-i}), \vartheta_i) \geq u_i (g (s_i` (\vartheta_i), s_{-i}), \vartheta_i) \text{ for all } s_i` \in S_i \text{ and all } s_{-i} \in S_{-i}.$$

Further, a mechanism with dominant strategy equilibrium is defined as follows:

Definition 6: The mechanism $\tau = (S_1,\ldots, S_m, g (.))$ implements the social choice function $f(.)$ in dominant strategies if there exists a dominant strategy equilibrium of τ, $s^* (.) = (s_1^* (.), \ldots, s_m^* (.))$, such that $g (s^* (\vartheta)) = f (\vartheta)$ for all $\vartheta \in \Theta$.

The dominant strategy equilibrium concept is robust due to the following assumptions and expectations: First, it can be asserted that a rational agent who has a dominant strategy will indeed play it. Unlike the Nash equilibrium concept, an agent need

---

[109] This meta-theoretical question is distinct from the theoretical question: which equilibrium should be chosen as optimal if one solution concept, such as Bayesian Nash equilibrium, predicts multiple equilibrium solutions for *a* game.

not correctly forecast other agents' play to justify her play of a dominant strategy. Second, agent *i*'s beliefs regarding the distribution of ϑ_{-i} do not affect the dominance of her strategy s_i^* *(.)*. Third, a mechanism designer need not know the probability density ϕ *(.)*.

Next, the concept of Bayesian Nash equilibrium is defined.

Definition 7: The strategy profile *(s₁* (.), …, sₘ* (.))* is a Bayesian Nash equilibrium of mechanism $\tau = (S_1, …, S_m, g (.))$ if, for all *i* and all $\vartheta_i \in \Theta_i$,

$$E_{\vartheta_{-i}} [\, u_i \, (g \, (s_i^* \, (\vartheta_i), \, s_{-i}^* (\vartheta_{-i})), \, \vartheta_i) \, / \, \vartheta_i] \geq E_{\vartheta_{-i}} [\, u_i \, (g \, (\hat{s_i}, \, s_{-i}^* \, (\vartheta_{-i})), \, \vartheta_i) \, / \, \vartheta_i] \text{ for all } \hat{s_i} \in S_i.$$

Definition 8: The mechanism $\tau = (S_1, …, S_m, g (.))$ implements the social choice function *f(.)* in Bayesian Nash equilibrium if there is a Bayesian Nash equilibrium of *M, s* (.) = (s₁* (.), …, sₘ* (.))*, such that $g (s^* (\vartheta)) = f (\vartheta)$ for all $\vartheta \in \Theta$.

The Bayesian implementation concept is a strictly weaker idea than the idea of dominant strategy implementation. Every dominant strategy equilibrium is necessarily a Bayesian Nash equilibrium (and not vice versa), which implies that any social choice function that is implementable in dominant strategies is also implementable in Bayesian Nash equilibrium. This is because Bayesian Nash equilibrium implementation requires that every agent *i* gets her highest payoff averaging over all possible types ϑ_{-i}'s payoffs that might arise for the other agents. On the other hand, dominant strategy equilibrium requires that every agent *i* gets her highest payoff for every possible payoff of ϑ_{-i}. Bayesian Nash equilibrium thus permits implementation of a wider range of social choice functions than the dominant strategy equilibrium concept. There are, however, two strong assumptions that need to be met to implement the Bayesian Nash equilibrium: First, this concept assumes that the agents as well as the mechanism designer know the density function of agents' types ϕ *(.)*. Second, agents have mutually correct expectations about each others' strategy choices.

Having formally outlined the concepts of dominant strategy and Bayesian Nash equilibriums in a principal-agent game of incomplete information, the following propositions are presented to describe adaptive mechanism designs, and to contrast them with other mechanisms.

Proposition 1: Incentives under regulatory mechanisms. Suppose there is a mechanism τ_R that is implemented under the rules of the game designed by a principal (who is the environmental regulator) to implement a collective choice social function $f\,(.)$. This mechanism assumes the polluter pays principle. Further, suppose that the expected utility of pursuing a non-cooperative strategy weakly dominates the expected utility of pursuing a cooperative strategy for agent i $[u_i\,(s_{nc},\,g\,(.)) \geq u_i\,(s_c,\,g\,(.))]$, then the outcome function $g\,(.)$ will be Pareto inferior because the non-cooperative strategies of the agents lead to less effective implementation of the collective social choice function.

Proposition 2: Contextual conditions of agents. Suppose some agent types (ϑ_i) pursue cooperative strategies (S_c) and other agent types (ϑ_j) pursue non-cooperative strategies (S_{nc}). Further, suppose that the expected utility of pursuing a non-cooperative strategy weakly dominates the expected utility of pursuing a cooperative strategy for agent i $[u_i\,(s_{nc},\,g\,(.)) \geq u_i\,(s_c,\,g\,(.))]$. Furthermore, suppose that some agents are expected utility maximizers and non-cooperative while others are altruistic and cooperative. Then the contextual conditions, such as the income level of agents' neighborhoods, the gender and aging configuration of agents' neighborhoods, and the racial profile of agents' neighborhoods, systematically differ between those agents' types who pursue cooperative strategies and those who pursue non-cooperative strategies.

Proposition 3: Incentives under adaptive mechanisms: Suppose there is an alternative adaptive mechanism τ_A that is implemented under the rules of the game designed by a principal (or a mechanism designer) to implement a collective choice social function $f\,(.)$. This alternative mechanism assumes that transfers of money can be carried out by a social planner from some agents to the other agents. Further, suppose the mechanism is designed in such a way that the expected utility of pursuing a cooperative strategy weakly dominates the expected utility of pursuing a non-cooperative strategy for agent i $[u_i\,(s_c,\,g\,(.)) \geq u_i\,(s_{nc},\,g\,(.))]$, then the multi-criteria outcome function $g\,(.)$ will be Pareto superior for τ_A than τ_R because the cooperative strategies of the agents lead to more effective and fairer implementation of the collective social choice function.

7.2 Decision theoretical implications

7.2.1 The modifications in the expected value hypothesis of rational decision theory

The results from phase I of this study confirm the earlier findings from controlled laboratory studies that people neither behave perfectly cooperatively nor perfectly non-cooperatively. The evidence in this study shows that about 42% of high-emitting vehicle owners cooperate while about 58% do not cooperate and pursue a strategy that attempts to avoid the community-mandated environmental laws. The findings are presented with utmost caution, as the empirical data that is needed to estimate the factors that may result in under or over-estimation of probability of cooperation is not currently available.

Despite these limitations, this study partially confirms the game theoretical expected value hypothesis that rational agents attempt to free ride in public goods decision games. This is obvious from the strategic behavior of the 58% non-cooperative vehicle owners observed in the Atlanta airshed. The upshot is that rest of the 42% people in the Atlanta airshed appear to be cooperating with the vehicle emission control laws, which is not predicted by the game theoretical framework. This however does not mean that predictions of game theory do not hold because we can perhaps never control for all the assumptions that are built into the game theoretical framework. Game theory, for example, assumes that rational agents have complete information about all the possible sets of actions and strategies (as listed in Figure 1.3). It is however possible that many vehicle owners do not have information about the loopholes in the current vehicle registration laws, which they can use to avoid the IM program regulations.

On the other hand, one cannot reject the social psychology theoretical hypothesis that cooperative vehicle owners could have pursued any of the available non-cooperative strategies, but they are cooperative enough to promote the provision of environmental goods even if it means higher costs for them. The 42% cooperation rate in this study affirms this hypothesis, but at the same time, social psychology theory fails to account for the non-cooperative strategic behavior of 58% of the high-emitting drivers.

One interesting rival hypothesis is provided by social justice and/or environmental justice theory. It is possible that these 58% of the non-cooperative high-emitters do not have enough income to incur the repair costs. This rival hypothesis cannot be directly tested as income data at the individual or household level is not

available. In this study, the analysis included the contextual conditions, such as the income level of the vehicle owner's neighborhoods at the census block level, which indirectly tested the environmental justice hypothesis [H_3 and H_4], the results of which are presented in section 6.4. The environmental justice hypothesis is confirmed in this study, as non-cooperative players come from lower income areas than the cooperative players. Furthermore, the environmental regulation targets people living in lower income areas to pay the costs of pollution clean-up, the benefits of which are to be shared by everybody in the airshed, including the people living in higher income areas who are not required to pay the pollution clean-up costs.

The expected value hypothesis thus needs to be modified in the light of the meta-question: Which values are used by the human decision makers [both regulators and regulated in this case] to measure the outcomes? Under strictly competitive and zero-sum contextual conditions, it is possible that the Darwinian instinct of maximizing the selfish interest might be *the* only value on which players measure the outcomes of their decisions. On the other hand, humans do not always live under strictly competitive and zero-sum contextual conditions: sometimes cooperation pays, as in case of protecting environmental resources. Furthermore, decision behaviors that affect our environments are not necessarily zero-sum. They can be both positive sum and negative sum. Positive contribution and cooperation by one decision maker can contribute more common/environmental benefits towards the entire society than the per capita cost of contribution, which is an example of a positive-sum game. Also, negative contribution and non-cooperation, such as bio-terrorism, can be negative-sum [higher collective cost than the individual cost], which may potentially destroy our environment not only for current generations, but also create conditions that future generations may never come into being.

The EV/EU hypothesis is thus neither provable nor disprovable under all contextual conditions of human decision makers because it is not clear which values we want to use to measure the outcomes of our decisions. Furthermore, different contextual conditions also strongly influence real-world human decisions. The problem is that the contextual conditions are dynamic in character and remain beyond the grasp of decision makers involving outcomes in future states of the world. If the EV/EU hypotheses are modified to allow for the explicit resolution of meta-decision problems, such as meta-level agreement on values on which the outcomes of actions are measured, it is shown

in this study that the EV/EU hypotheses proposed by game theory *converge* with the social psychology and political science hypotheses about human decision making. Meta-decision models thus provide one important methodology for convergence among the descriptive and normative decision theories.

7.2.2 Bridging descriptive with normative decision theories in meta-decision models

Meta-criteria heuristics act as principle determinants of meta-choices. If we accept context-sensitivity as a meta-criteria heuristic for environmental management decision problems, then the set of alternatives and criteria in a decision problem is chosen in the light of the context of a decision problem, and these sets are open to change as context changes. Similarly, context determines the choice of the decision rule and the weights to be assigned to the set of decision criteria.

Formally, meta-decision models require input of meta-criteria heuristics, which can be denoted by a set, H, written in the pragmatics of language. For example, H may contain the following three elements: context-sensitivity, process orientation and adaptability. The meta-choice decision problem, such as the choice of the sets of alternatives [A], values [z], outcomes [f(z)] and weights [w] is resolved in the light of the constraints specified in H.

The set of alternatives is thus drastically reduced from an infinite set to a finite set depending upon the context of the decision problem. Similarly, the criteria set is delimited by H. A and z sets, however, are not fixed; rather they are adaptive and change within the long-term space-time horizon. At the same time, the sets A and z are evaluated at a certain moment in space-time in the light of constraints imposed under meta-criteria heuristics.

The third implication of H is its effect on the meta-choice decision problem of choosing a weighting methodology to ascertain the weights among mostly incommensurate decision criteria chosen in the set z with respect to the alternatives in the set A. In Section 3.3, the weighting methodology that is employed in the 12 most widely applied decision algorithms was discussed, and it was concluded that each of these decision algorithm requires exogenous determination of weights, albeit a different methodology and sometimes a different heuristic is used to characterize their exogenous weighting assumptions. One solution to the meta-choice decision problem of choosing a weighting methodology will be to ascertain the weights as per the methodology of each

decision algorithm and then compare the proposed solutions of each of these alternatives.

Another idea, seldom pursued in previous research, is to conduct a sensitivity analysis of all possible permutations and combinations of weighting functions for each element of the criteria set z with respect to each element of the alternative set A. Further, if we choose "robustness" as an additional component of context, then sensitivity analysis will choose a particular policy alternative that is robust across all the decision criteria under a majority of the weighting combinations. Employment of sensitivity analysis does not however mean that the meta-choice decision problem of weighting methodology is resolved. The weighting problem is rather an "un-decidable" decision problem, requiring an exogenous choice.

The fourth implication of the set of meta-criteria heuristics in meta-decision models concerns the meta-choice decision problem of choosing a decision algorithm/rule to evaluate the environmental management decision problem φ (A, f). 12 decision algorithms (a subset of about 135 decision algorithms discussed in previous literature) are briefly presented in appendix A. Next to be discussed is how the set of meta-criteria heuristics can influence the meta-choice of a decision algorithm.

Assuming that context-sensitivity is used as a meta-criteria heuristic, the MDM permits employment of all those decision rules which are applicable and measurable in the given context of the environmental decision problem. The decision algorithm of cost-benefit analysis cannot be employed in the context of air quality management decisions because the damage function accruing from vehicular emissions to humans, animals, plants and broader eco-systems cannot be empirically measured for all present and future space-times and concatenated to the scalar outcome of net present monetary values. Due to lesser informational requirements, the decision algorithm of cost-effectiveness is perhaps more appropriate in evaluating the policy alternatives in air quality management problems. This algorithm, however, will also require statistical assumptions for empirically measuring the cost-functions, especially in the case of *ex ante* evaluation of policy alternatives. In brief, the choice of the meta-criteria heuristics set H determines the choice of decision algorithms that are employed to evaluate an environmental management decision problem.

There remains, however, a complex problem in that different decision algorithms may recommend conflicting policy alternatives as optimal choices. Despite the issue of

non-transitivity, in proposition 5, the construction of consensus, democratic and possible resolution spaces is proposed as a temporary measure to resolve complex environmental management decisions in the given environmental and social contexts.

Formally, the decision problem φ (A, f) is bounded by the set of meta-criteria heuristics H and reduced to a decision problem of the form $\varphi`$ (A`, f`), where A` is a subset of A and f` is a subset of f. Next, the decision problem $\varphi`$ (A`, f`) can be evaluated by the set of multiple decision algorithms K, which is finite and assumed to be common knowledge.

Proposition 5: Sensitivity analysis of multiple decision rules in environmental management decision problems. There are n decision rules { K_1, K_2, …, K_n} in a compact and closed set of decision algorithms K. Each element K_k (where k = 1, 2,…n) as a decision algorithm generates rankings over the finite set A`, such that $A`_{ik} > A`_{jk}$ {for i = 1,2,…l and j = 1,2,…l and i ≠ j and k = 1,2,….n}, i.e. $A_i$ is preferred over $A_j$ according to the decision rule $K_k$. It is possible that according to the decision rule $K_l$ (where l = 1, 2,…n) $A_j$ is preferred over $A_i$, mathematically $A`_{il} > A`_{jl}$ {for i = 1,2,…l and j = 1,2,…l and i ≠ j and l = 1,2,….n and l ≠ k}. Let us define a subset of <u>consensus</u> resolution alternatives A`` ∈ A`, such that A`` is the optimal solution for ALL of the decision algorithms K_1 ∩ K_2 ∩,……..K_v. The consensus resolution set A`` is required to be strictly transitive for all decision algorithms and it is possible in normal practice that A`` will be found empty. Secondly, let us define a subset of <u>democratic</u> resolution alternatives A``` ∈ A`, such that A``` is the optimal solution for a MAJORITY of the decision algorithms K_1 ∩ K_2 ∩,……..K_W, for w ∈ v. The democratic resolution set A``` is not required to be strictly transitive for all decision algorithms and it is possible in normal[110] practice that A``` will have at least one element. Thirdly, let us define a subset of <u>possible</u> resolution space A```` ∈ A`, such that A```` is the optimal solution for at least ONE of the decision algorithms K_1 U K_2 U,……..K_v. Given these definitions, meta-choice decision problem in environmental management can be defined as a problem of choosing between a consensus, a democratic or a possible resolution space. There is no algorithmic solution

---

[110] Under exceptional circumstances, it is possible that the democratic decision rule will not have one element, such as 5 out of 10 decision rules might prefer one alternative and the remaining 5 might prefer the other one. A simple answer would be to employ an odd number of decision rules. Subtler is the meta-problem of choosing an additional decision rule that follows the meta-criteria heuristics of the decision problem.

to decide if A`` > A``` > A````, or if A```` > A``` > A``, i.e. whether a consensus solution is preferred over a democratic solution or any possible solution is preferred over a consensus solution. My proposition, based on the meta-criteria heuristics set H, however, is as follows: In environmental management decisions, we *should* prefer consensus resolution space over the democratic resolution space whenever possible (i.e. when A`` is not empty), and democratic resolution space over the possible resolution space, otherwise. Mathematically, A`` > A``` > A````.

7.3 Methodological implications

7.3.1 Linking conventional with natural contexts in statistical decision models involving risky and uncertain outcomes

While knowledge about uncertain future states of the world remains elusive on many important issues of interest to environmental policy, it is clear from this study that in human decision behaviors – the conventional contexts – intertwine and interact with their environments – the natural contexts. We can not separate the study of our natural context, such as that studied by atmospheric chemistry, physics and biology, from a serious investigation of our conventional contexts, such as policy mechanisms, political governance regimes, societal institutions, and above all, our individual decision behaviors.

This study, with its unabashedly interdisciplinary perspective, has shown that natural and conventional contexts can be scientifically modeled together. It is only our imagination that can limit the synthesis of knowledge from undertaking multidisciplinary pursuits of our decisions that affect our environments. Importantly, statistical decision-aiding models can be used, first to *describe* the current state of environment and our decision-making effect on it in a synergistic manner; and secondly, the evidence from these multidisciplinary, statistical decision-aiding models can be used at the meta-level of reflection as an evidence to think about our future.

7.3.2 Measurement of latent variables through quasi-experimental methodologies in indirectly observed stochastic systems

Human decision behaviors, as also their environments, are complex and stochastic in nature. Due to incomplete information, ironically in this age of information

glut, it is not always possible for designers of public policy mechanisms to directly observe the variables of interest. Let's refer to these variables as "latent variables".

Quasi-experimental methodologies, as used in this study, provide one interesting methodology to measure the latent variables. Cooperative and non-cooperative decision behaviors are examples of latent variables; and it will perhaps remain a challenge for public policy evaluators for a long time to come to find precise parametric location of such latent variables. On the other hand, newer technologies of data gathering, such as remote sensing data, and data analysis methodologies, such as spatial analysis in GIS systems, can be combined in quasi-experimental studies to measure many latent variables of policy interest at a finer contextual level.

7.4: Conclusions

The decision makers/agents affected by regulatory environmental policy interventions are neither perfectly cooperative nor non-cooperative. In a case-study of IM program intervention in the Atlanta airshed, it was found that about 42% of the high-emitting drivers play cooperatively while the other 58% do not cooperate and attempt to free ride on the common resource of clean air.

There is no statistical difference in the vehicular tail-pipe CO and NO emissions produced by vehicle owners in cooperative and non-cooperative groups. However, vehicles in cooperative groups emit less HC emissions as compared to the vehicles in non-cooperative groups.

The IM program intervention, due to its assumption of the 'polluter pays principle', targets high-emitting vehicle owners to bear the repair costs on the emission control systems of their vehicles. The high-emitting vehicle owners, however, reside in lower income areas and own older vehicles than normal-emitting vehicle owners. The IM program intervention therefore targets drivers in lower income areas, which is not fair. The 'polluter pays principle' thus may not always lead to fair outcomes. If the value of fairness is desirable in evaluating the public policies, the 'polluter pays principle' would need to be modified/relaxed in the light of the contextual conditions of the affected/regulated decision makers.

Though both cooperative and non-cooperative high-emitting vehicle owners come from lower income areas than those of normal emitting vehicle owners, it is found

in this study that cooperative vehicle owners come from relatively higher income neighborhoods as compared to the non-cooperative vehicle owners. These results suggest that non-cooperative vehicle owners are not cooperating with the environmental policy laws because they are concerned that an unfair public policy is targeting them for producing a benefit that is to be shared by even those who are not targeted by this public policy. It can be inferred that a concern for fairness induces decision makers to exhibit non-cooperative decision behaviors.

The regulatory policy mechanisms should be made more adaptive to changes in the natural, conventional and technological contexts of the decision makers. The adaptive mechanism designs explicitly take into account multiple values, on which the outcomes of public policies are measured. Meta-decision models act as tools of adaptive mechanism designs to descriptively analyze the current outcomes and normatively prescribe the desirable outcomes in the space-time of policy horizons.

In the case of high-emitting vehicle owners in the Atlanta airshed, the IM regulatory program can be adapted to become more effective in reducing vehicular emissions as well as fairer in distribution of costs and benefits on all income groups of the society. This adaptation will require that (a) current rules of the game be changed, such as disallowing IM test failures from registering anywhere in the state of Georgia and requiring an emissions test on every change of vehicle ownership inside the 13-county IM program area and (b) transfers from normal-emitting high-income groups of the society be made to the high-emitting low-income vehicle owners, which will change the incentive structure of the regulatory mechanism design and result in higher cooperation, effective reduction in environmental pollution and fairer distribution of policy intervention costs and benefits. The adaptive mechanisms, as aided by meta-decision models, provide methods for public policy analysis to design policy interventions that help improve the outcomes, which are desirable according to the multiple values cherished by human societies.

METHODS TO CONVERT EMISSION CONCENTRATION RATIOS INTO MASS EMISSION FACTORS AND MASS EMISSION RATES

Remote sensors measure CO, HC and NOx as concentration ratios – such as % CO/CO_2, $\%HC/CO_2$, $\%NO/CO_2$ – which are denoted as CR_{CO}, CR_{HC} and CR_{NOx} respectively. These emission concentration ratios can be converted into mass emission factors (Y_{CO}, Y_{HC} and Y_{NOx}) that are measured in units of grams of pollutant per gallon of gasoline burned by an automobile. The conversion process is based on a stoicheometeric theory of carbon balance. Singer and Harley (2000:1784) proposed the following generalized stoicheometeric equation to convert concentration ratios into mass emission factors:

(A.1): $Y_P = [CR_P / (1+CR_{CO} + 3\ CR_{HC})] \cdot [(w_c\ \rho_f / 45.4249)\ M_P]$; for P = CO, HC and NOx.

Where Y_P is the mass emission factor for CO, HC and NOx in grams per gallon (gg^{-1}); CR_P is the molar exhaust concentration ratio of pollutant P to CO_2 measured by the remote sensor; $w_c = 0.85$ is the carbon mass fraction and $\rho_f = 750\ gl^{-1}$ is the density of gasoline; M_P is the molecular mass of the pollutant being considered (28 g mol^{-1} for CO, 44 g mol^{-1} for HC as propane, 30 g mol^{-1} for NOx as NO); and 45.4249 is the product of 12 (for atomic mass of carbon) and 3.7854118 (for converting the gasoline volume in liters to US gallons). The first quotient of equation A.1 -- $[CR_P / (1+CR_{CO} + 3\ CR_{HC})]$ – reduces to the molar ratio of CO, HC or NO to total carbon atoms in vehicle exhaust; and the second quotient -- $[(w_c\ \rho_f / 12)\ M_P]$ – defines the molar concentration of carbon atoms per gallon of un-burned gasoline. Equation A.1 also includes a factor of 3 in denominator of first quotient to convert from moles of propane to moles of carbon, because HCs were measured as propane[111].

---

[111] Singer and Harley (2000: 1785), in order to convert HC emission factor –i.e. EF_{HC} -- into VOC emission factors – i.e. EF_{voc} further multiplied EF_{HC} (estimated through equation 4.1) by a factor of 2.0 ± 0.1.

Pokharel et al. (2001) estimated following specific equations A.2 to A.4 to convert emission concentration ratios (CR_p) into mass emission factors (Y_P) , which are employed in this study to measure the dependent variables for equations 1.7, 1.8 and 1.9:

A.2: Y_{CO} (gram/gallon) = $5506.CR_{CO}/(15 + 0.285CR_{CO} + 2.87\ CR_{HC})$

A.3: Y_{HC} (gram/gallon) = $8644.CR_{HC}/(15 + 0.285CR_{CO} + 2.87\ CR_{HC})$

A.4: Y_{NO} (gram/gallon) = $5900.CR_{NO}/(15 + 0.285CR_{CO} + 2.87\ CR_{HC})$

The equations A.2 to A.4 present two important constraints for converting remotely sensed pollutant emission concentration ratios into pollutant mass emission factors: First, mass emission factor for CO can only be measured if and only if both CO and HC concentration ratios are available for an observation. Similarly, mass emission factor for HC can only be measured if and only if both CO and HC concentration ratios are available for an observation. Furthermore, mass emission factor for NO can only be measured if and only if NO, CO and HC concentration ratios are available for an observation. Second, the equations are defined for strictly positive concentration ratios; i.e. $CR_{CO} > 0$, $CR_{HC} > 0$ and $CR_{NO} > 0$. Remote sensors however also report negative concentration ratios for the observations when mean value is smaller than the standard error of measurement. The negative concentration ratios are converted into missing values in the remote sensing sample before estimating pollutant emission factors, as in equations A.2, A.3 and A.4. Note that both the above-mentioned constraints resulted in reducing the remote sensing sample size from 775,606 observations for CR_{CO} into 466,640 observations for Y_{CO} between 1997 and 2001; 741,869 observations for CR_{HC} into 466,640 observations for Y_{HC} between 1997 and 2001; and 136,486 observations for CR_{NO} into 89,408 observations for Y_{NO} between 1999 and 2001. Their descriptive statistics are presented in table 5.1. Limitations and biases that arise due to these two constraints are discussed in section 5.6. For a meaningful policy analysis, it is important to convert remote sensor measured emission concentration ratios into mass emission factors. The most important results of this study in sections 6.2.2; 6.2.3 and 6.2.4 are reported in terms of changes in emissions factors (gg[-1]) as the independent parameters change in the models estimating equations 1.7, 1.8 and 1.9.

Once the concentration ratios of pollutants (CR_{CO}, CR_{HC} and CR_{NO}) measured by remote sensors in units percentage of pollutant per percentage of CO_2 are converted into mass emissions factors (Y_{CO}, Y_{HC} and Y_{NO}) in units grams of pollutant per gallon of

gasoline burned, then it is a usual practice among environmental policy analysts to generalize the study results to the study area by estimating mass emission rates (ER_{CO}, ER_{HC} and ER_{NOx}) in units (grams or) tones of pollutant per (day or) year. Mass emission rates can be estimated through two methods –fuel based and VMT based -- which are described below. Both methods require fuel economy (FE) measures in units of miles per gallon to convert mass emission factors into mass emission rates. At the moment, monthly fuel sales data for the Atlanta area between 1997 and 2001 is not available, while VMT data for the state of Georgia for the study period is available from Bureau of Transportation Statistics (BTS).[112] This study, therefore, uses VMT based method to estimate mass emission rates for eleven fleet types during the study period, as explained in method 2 below.

Method 1: Fuel-use based mass emission rates:

Fuel-use based method employs fuel/gasoline-sales data to convert mass emission factors into mass emission rates (Singer and Harley 1996, 2000).[113] The fraction of total fuel f_{ij} used by vehicles of each model year i and vehicle type j[114] is calculated as shown in equation A.5:

A.5: $f_{ij} = [(v_{ij}/FE_{ij})/\sum_i \sum_j (v_{ij}/FE_{ij})$

Where v_{ij} is the fraction of vehicles by each model year and type ($v_{ij} = n_{ij}/N$ where n_{ij} is the count of model year i and type j vehicles and N is the total number of remote sensor measurements) and FE_{ij} is the average fuel economy of model year i and type j vehicles.

Fleet average emission factors Y_{aveP} are calculated using the fuel fractions f_{ij} and emission factors $Y_{P, ij}$ for each vehicle model year and type, as shown in equation A.6:

A.6: $Y_{aveP} = \sum_i \sum_j f_{ij}.Y_{P, ij}$ (in grams per gallon)

---

[112] The appropriate data can be downloaded from the BTS website http://www.transtats.bts.gov/
[113] Normally one has to be careful in calculating the fuel sales for the area of study for specific times. Singer and Harley (2000: 1785) used statewide released monthly fuel sales data (in units of liters per month) which was adjusted to represent fuel used by cars, LDGV and LDGTs in the IM program area for the study period. They used population percentage (from census data) and vehicle registration percentage (from vehicle registration data) to estimate fuel use for program/study area. Further, gasoline use by construction and farm equipment, boats and other off-road engines was also deducted from the estimates of fuel use in program area.

[114] Singer and Harley (2000: 1786-7) did not separate cars and trucks for estimating fuel-use fractions (equation A.5) by vehicles of each model year, which biases the results because trucks have, on average, compared to cars, higher (NO) emissions factors as well as lower fuel economy.

Total mass emissions rate of CO, HC and NO in the program area for the period of study is calculated as the product of the fleet average emission factors Y_{aveP} and the total gasoline (G_{ij}) used by i cars and j trucks in the program area. Fleet average mass emission rates ER_{avePIJ} for each model year [I] and vehicle class [J] are estimated by using equation A.7:

A.7: $ER_{ave\ Pij} = [\sum_I \sum_J (Y_{ave\ Pij}) \cdot (G_{ij})]$ (in tones per year)

Method 2: VMT based mass emission rates for 11 fleet types:

Suppose Y_{PQIJT} represents emission factor (in grams per gallon) for pollutant P [i.e. CO, HC and NO], fleet type Q, vehicle model year i [observation year – vehicle age], and vehicle type j [i.e. car or truck] in time T [1997, 1998....2001]. Reduced[115] OLS models were used to estimate equation A.8 for measuring Y_{PQIJT} in the Atlanta airshed between 1997 and 2001. Estimated equations are presented in table A.1.

A.8: $Y_{PQIJT} = [\alpha_0 + \sum_{q=2}^{11} \beta_q Q_q + \sum_{r=1}^{2} \gamma_r R_r + \varepsilon_1]_T$

Where α_0 represents emission factor of control fleet passenger car of age 0 in time t (in 1997 it will be model year 1997, and so on). β_q for q = { 2,3,…11} respectively represent emission factors for ineligible, waived, rest-of-GA, missing, retest pass, migrated pass, retest fail, migrated fail, missing fail and missing pass passenger cars of age 0 in time T. γ_r for r = {1,2} respectively represent coefficients on the variables vehicle age and vehicle type in time T.

Further suppose VMT_{QIJT} represents vehicles miles traveled by a vehicle of fleet type Q, model year i, vehicle type j in time T. Ideally, if odometer data was correctly reported in vehicle registration data, VMT_{QIJT} could have been estimated from there. But, unfortunately, as extensively discussed in section 5.4.1, odometer data is not correctly reported in registration data. As a second best option, I used aggregate VMT data for the state of Georgia released by BTS for each year between 1997 and 2000, which is denoted as $VMT_{T,\ GA}$, and the data values are reported in table A.2. The total number of vehicles registered in the state of GA during the study period are also reported in table A.2.

---

[115] Full model, as used in estimating equations 1.7 to 1.9 was not used to estimate equation A.8 because fuel economy data for each vehicle manufacturer, country of vehicle manufacturer, vehicle type and model year of the vehicle is not available. Sales-weighted fuel economy data for model years 1974 and above is available for both cars and trucks at the USA level, which has been used in this study.

Table A.1: Reduced OLS regression models predicting parameters of equation A.8. Outcome variables CO, HC and NO (grams/gallon)

Dependent	1997		1998		1999			2000			2001		
	CO	HC	CO	HC	CO	HC	NO	CO	HC	NO	CO	HC	NO
Valid N	80032	80032	73496	73496	81598	81598	5845	113647	113647	16088	94175	94175	66698
Constant	22.61* / 3.81	17.66* / 0.72	8.67* / 3.79	10.77* / 0.53	9.36* / 3.30	7.14* / 0.35	6.46* / 0.91	-0.47 / 2.23	4.69* / 0.19	7.96* / 0.58	-26.64* / 2.46	-0.61* / 0.06	8.02* / 0.26
Vehicle age	37.05* / 0.31	2.50* / 0.06	32.73* / 0.31	1.78* / 0.04	27.96* / 0.27	1.33* / 0.03	2.63* / 0.09	23.30* / 0.19	1.12* / 0.01	2.68* / 0.05	23.80* / 0.26	0.50* / 0.01	2.24* / 0.02
Vehicle type	51.62* / 3.24	1.55* / 0.62	42.37* / 3.10	1.43* / 0.43	34.41* / 2.72	0.63* / 0.29	5.00* / 0.8	20.36* / 1.86	0.03 / 0.16	5.20* / 0.49	14.73* / 2.07	0.45* / 0.05	4.66* / 0.22
Ineligible	39.50* / 3.78	4.31* / 0.72	45.00* / 3.70	3.21* / 0.52	17.54* / 3.17	0.12 / 0.34	1.43 / 0.86	24.67* / 2.13	1.75* / 0.18	2.00* / 0.56	46.87* / 2.75	1.20* / 0.06	-1.87* / 0.29
Waived	160.43* / 34.52	24.76* / 6.59	138.88* / 28.07	0.311 / 3.95	166.56* / 21.27	15.99* / 2.31	6.93 / 10.11	35.40 / 19.04	3.84* / 1.66	17.69* / 5.72	22.14 / 17.27	1.34* / 0.41	4.92* / 1.88
Rest-of-GA	69.06* / 5.50	7.24* / 1.05	71.53* / 5.52	6.34* / 0.77	45.72* / 4.96	2.14* / 0.53	3.26* / 1.41	53.45* / 3.37	2.14* / 0.29	4.04* / 0.87	49.52* / 3.54	0.99* / 0.08	2.91* / 0.38
Missing	8.67 / 7.03	0.82 / 1.34	55.27* / 7.13	5.33* / 1.00	29.47* / 9.48	2.13* / 1.03	4.87* / 2.46	33.43* / 7.27	3.45* / 0.63	0.42 / 2.13	1.07 / 7.35	0.30 / 0.17	0.07 / 0.78
Retest pass	169.17* / 12.69	3.63 / 2.42	125.68* / 11.18	6.37* / 1.57	126.53* / 8.97	6.50* / 0.97	17.05* / 2.67	80.26* / 6.14	2.85* / 0.53	16.50* / 1.70	83.28* / 5.64	1.55* / 0.13	19.53* / 0.58
Migrated pass	NA	NA	62.45* / 16.99	0.68 / 2.39	32.60* / 11.33	1.93 / 1.23	10.14* / 4.40	44.54* / 7.76	1.84* / 0.67	5.92* / 1.95	27.06* / 9.04	1.03* / 0.22	3.10* / 0.97
Retest fail	257.53 / 25.23	11.25* / 4.82	252.27* / 19.40	12.49* / 2.73	260.15* / 20.51	13.11* / 2.23	25.09* / 6.42	198.40* / 16.98	15.86* / 1.48	24.83* / 5.27	82.81* / 11.16	2.87* / 0.27	18.81* / 1.15
Migrated fail	NA	NA	314.23* / 40.41	4.83 / 5.69	215.88* / 26.93	4.41 / 2.92	9.33 / 10.15	210.36* / 19.44	5.96* / 1.69	9.29 / 5.27	177.53* / 23.94	1.96* / 0.58	13.59* / 2.44
Missing fail	NA	NA	178.75* / 27.12	7.27 / 3.81	265.58* / 17.69	9.15* / 1.92	2.817 / 5.27	151.47* / 11.95	5.10* / 1.04	13.90* / 3.72	45.98* / 11.74	1.88* / 0.28	11.06* / 1.22
Missing pass	NA	NA	14.87 / 8.99	-0.15 / 1.26	21.18* / 6.82	2.09* / 0.74	3.81* / 1.83	5.69 / 4.68	1.17* / 0.40	3.06* / 1.36	1.16 / 4.33	0.14 / 0.11	-1.05* / 0.45
Adj-R²	16.40%	2.40%	14.50%	2.50%	13.40%	3.00%	14.70%	12.80%	4.30%	16.10%	10.70%	8.10%	16.60%
F-test for model fit	1968.7	243.5	1040.9	158.1	1050.3	208.44	85.2	1388.6	425.96	258.02	937.27	696.51	1105.4

A * indicates that the coefficient value is statistically significant at 95% confidence level, with 5% probability of type one error.

Table A.2: Annualized vehicle registration and VMT statistics for the state of Georgia. (Source BTS)

	1997	1998	1999	2000	2001
Total vehicles	6317832	6979592	7059719	7243077	7396731
Cars	3688005	4032998	4011725	4066530	4084746
Trucks	2537703	2843253	2943465	3070459	3201501
Buses	16499	17068	17520	18017	18538
Motorcycles	75625	86273	87009	88071	91946
Total VMT (million miles)	93840	97030	98859	105010	107897
Rural VMT (million miles)	39645	40618	42904	47523	49690
Urban VMT (million miles)	54195	56412	55955	57487	58207
VMT/Vehicle (Miles/year)	14853.19	13901.96	14003.25	14497.98	14587.12
Trucks/Cars ratio	0.4076	0.4135	0.4232	0.4302	0.4394

Next, Vehicle Miles Traveled in the 13 county area during the study period, denoted as $VMT_{T, \text{13 county area}}$, were imputed by using equation A.9:

A.9: $VMT_{T, \text{13 county area}} = VMT_{T, GA} * [f_{inside} + f_{outside}]$

Where f_{inside} represents fraction of total GA vehicles registered inside 13 county area and $f_{outside}$ represents fraction of rest of GA registered vehicles observed visiting inside the 13 county area.[116] f_{inside} was estimated from the vehicle registration data, while $f_{outside}$ was estimated from both the vehicle registration and the remote sensing sample data.[117] Below is the estimated equation A.9 for each year of the study:

A.9.1: $VMT_{1997, \text{13 county area}} = 93840 * [0.403 + (0.1140*0.597)] = 44,204.0827$ million miles

A.9.2: $VMT_{1998, \text{13 county area}} = 97030 * [0.408 + (0.1118*0.592)] = 46,010.2288$ million miles

A.9.3: $VMT_{1999, \text{13 county area}} = 98859 * [0.417 + (0.1065*0.583)] = 46,769.1054$ million miles

A.9.4: $VMT_{2000, \text{13 county area}} = 105010 * [0.411 + (0.1145*0.589)] = 50,240.9844$ million miles

A.9.5: $VMT_{2001, \text{13 county area}} = 107897 * [0.407 + (0.1135*0.593)] = 51,176.0866$ million miles

Next, suppose that v_{QIJT} represents the fraction of vehicles by fleet type Q, model year I, vehicle type J in time T, then v_{QIJT} is estimated from the remote sensing sample by using equation A.10:

A.10: $v_{QIJT} = [n_{QIJ} /N]_T$,

---

[116] An ideal analysis would also include fraction of out-of-GA state vehicles found visiting inside the 13 county area; but this is not included in the analysis due to the data restrictions.

[117] $F_{outside}$ is estimated as being equal to $\{[(Q_4 + Q_7 + Q_9)/\sum_{q=1}^{11}Q_q]*f_{rest\text{-}of\text{-}ga}\}$ from the remote sensing sample and vehicle registration data, where $f_{rest\text{-}of\text{-}ga}$ represents the fraction of vehicles registered outside the 13 county area in the state of Georgia.

Where n_{QIJ} represents the total number of Q fleet type vehicles by model year I and vehicle type j observed in time T, and N represents the total number of vehicles observed in time T in the remote sensing sample. VMT_{QIJT} is then estimated by equation A.11.

(A.11): $VMT_{QIJT} = v_{QIJT} * VMT_{T, \text{13 county area}}$

Where v_{QIJT} is estimated by equation A.10 and $VMT_{T, \text{13 county area}}$ is estimated by equation A.9. This equation assumes that vehicles of all fleet types, model years and types travel on average equal distance in a given year in the 13-county Atlanta area. Sales-weighted Fuel Economy data FE_{IJ} for model years I and vehicle types j is gathered from Singer and Harley (2000) and converted in miles per gallon, which is shown in figure A.1. Sales weighted fuel economy improved exponentially during the late 1970s and 1980s, but it is noticeable in figure A.1 that the exponential trend of improved fuel economy has tapered off during the 1990s. Trucks on average have lower fuel economy standards than the passenger cars and the difference between the two is shown in figure A.1.
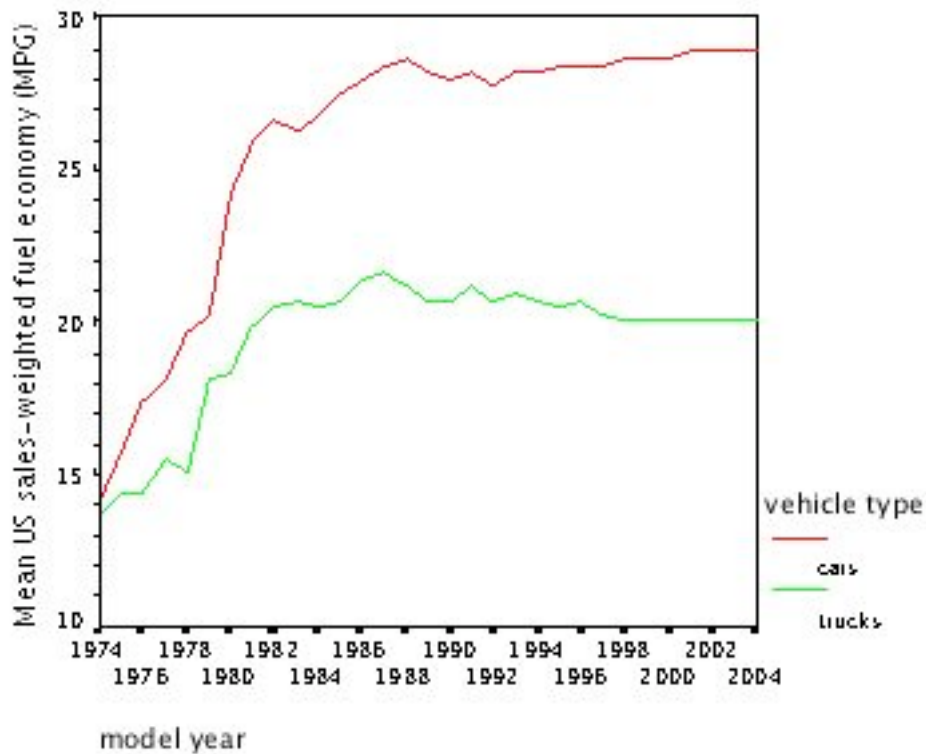

Figure A.1: Mean sales-weighted fuel-economy standards by vehicle model-year in the USA

ER$_{PQT}$ represents total mass emissions rates of the pollutant P (CO, HC and NO) in tons per year of fleet type Q$_q$ in time T and is estimated by using equation A.12.

(A.12): ER$_{PQT}$ (tons per year) = $\sum_i \sum_j$ [(Y$_{PQIJT}$ * VMT$_{QIJT}$)/FE$_{IJ}$]

Where Y$_{PQIJT}$ is estimated through equation A.8 [estimators are shown in table A.1] in grams per gallon, and VMT$_{QIJT}$ is estimated through equation A.11 in million miles and FE$_{IJ}$ is measured in miles per gallon. The estimated values for ER$_{PQT}$ in tons per year are shown in table A.3. The results from table A.3 are discussed in detail in section 6.2.4.

Table A.3: Estimated mean CO, HC and NO emission rates (in tons per year) for eleven fleet types in five years of the study

Panel A: Mean CO emission rates

	1997	1998	1999	2000	2001
Control	86,407.35	88,745.00	77,687.78	74,333.41	131,321.43
Ineligible	288,786.01	224,804.63	188,131.27	157,329.07	47,864.03
Waived	1,855.66	2,331.20	2,719.81	1,366.50	2,165.97
Rest of GA	70,471.89	59,086.88	43,264.16	41,723.61	38,787.59
Missing	28,468.72	33,078.88	8,705.94	6,476.68	8,123.43
Retest pass	13,116.39	14,257.20	14,316.41	13,491.38	19,452.58
Migrated pass	0.00	3,810.03	5,892.47	5,742.29	4,538.54
Retest fail	3,195.99	5,525.70	3,091.38	2,230.54	4,252.01
Migrated fail	0.00	1,487.18	1,833.02	1,811.48	1,323.52
Missing fail	0.00	2,318.74	5,093.46	4,672.21	4,372.58
Missing pass	0.00	13,360.24	17,601.94	15,185.47	18,850.88
Total	492,302.01 (1348.77 t/d)	448,805.68 (1229.60 t/d)	368,337.64 (1009.14 t/d)	324,362.64 (888.66 t/d)	281,052.56 (770.01 t/d)
IM eligible total	133,044.11	164,914.17	136,942.21	125,309.96	194,400.94
Cooperative total	13,116.39	18,067.23	20,208.88	19,233.67	23,991.12
Non-cooperative total	3,195.99	22,691.86	27,619.80	23,899.70	28,798.99

Panel B: mean HC emission rates (VOC emission rate $\cong$ 2*HC emission rate)

	1997	1998	1999	2000	2001
Control	11,449.06	9,170.78	6,513.26	5,909.85	2,788.53
Ineligible	37,892.73	22,907.54	14,901.89	12,931.90	1,172.56
Waived	206.93	138.90	206.32	92.14	51.56
Rest of GA	8,333.41	5,625.64	3,151.81	2,777.56	816.77
Missing	3,465.57	3,070.42	686.84	519.8	184.15
Retest pass	1,053.61	1,058.62	912.8	793.7	398.29
Migrated pass	0.00	306.55	441.77	385.33	109.17
Retest fail	258.69	379.53	184.56	158.42	106.99
Migrated fail	0.00	76.18	88.27	88.06	22.57
Missing fail	0.00	156.95	265.13	248.03	105.38
Missing pass	0.00	835.85	1,380.18	1,157.14	414.76

Total	62,660.00	43,726.96	28,732.83	25,061.93	6,170.73
	(171.67 t/d)	(119.80 t/d)	(78.72 t/d)	(68.66 t/d)	(16.91 t/d)
IM eligible total	16,433.86	15,193.78	10,679.13	9,352.47	4,181.40
Cooperative total	1,053.61	1,365.17	1354.57	1179.03	507.46
Non-cooperative total	258.69	1448.51	1918.14	1651.65	649.7

Panel C: mean NO emission rates (in tones per year)

	1999	2000	1999-2000	2001
Control	10,135.79	13,567.56	23703.35	24,092.44
Ineligible	24,328.96	27,595.92	51,924.88	8,570.72
Waived	241.57	188.03	429.6	299.97
Rest of GA	5,049.38	6,328.56	11,377.94	5,989.20
Missing	1,148.34	949.43	2097.77	1,266.79
Retest pass	1,731.61	2,239.81	3971.42	3,330.38
Migrated pass	882.31	939.29	1821.6	778.36
Retest fail	326.12	309.32	635.44	747.21
Migrated fail	158.78	188.1	346.88	151.36
Missing fail	352.28	595.55	947.83	676.11
Missing pass	2,245.67	2,676.22	4921.89	3,132.12
Total	46,600.81	55,577.79	102,178.60	49,034.66
	(127.67 t/d)	(152.27 t/d)	(279.94 t/d)	(134.34 t/d)
IM eligible total	17,222.47	21,653.31	38,875.78	34,474.74
Cooperative total	2,613.92	3,179.10	5,793.02	4,108.74
Non-cooperative total	3,082.85	3,769.19	6,852.04	4,706.8

REFERENCES

Alker, H. R. (1969). A Typology of Ecological Fallacies. <u>Quantitative Ecological Analysis in the Social Sciences</u>. M. Dogan and S. Rokkan. Cambridge, MIT Press: 69-86.

Allais, M. (1953). "Le Comportement De L'homme Rationel Devant Le Risque, Critique Des Postulates Et Axiomes De L'ecole Americaine." <u>Econometrica</u> 21: 503-46.

Allais, M. (1979). The So-Called Allais Paradox and Rational Decisions under Uncertainty. <u>The Expected Utility Hypothesis and the Allais Paradox</u>. M. Allais and O. Hagen. Dordrecht, Reidel.

Ando, A., V. McConnell, et al. (2000). "Costs, Emissions Reductions and Vehicle Repair: Evidence from Arizona." <u>Journal of the Air and Waste Management Association</u> 50(4): 509-521.

Ando, A., V. McConnell, et al. (1999). "Costs, Emissions Reductions, and Vehicle Repair: Evidence from Arizona."

Andreoni, J. (1988b). "Why Free Ride? Strategies and Learning in Public Goods Experiments." <u>Journal of Public Economics</u> 37: 291-304.

Arora, S. and T. Carson (1996). "Why Do Firms Volunteer to Exceed Environmental Regulations? Understanding Participation in Epa's 33/50 Program." <u>Land Economics</u> 74: 413-432.

Aumann, R. J. (1987). "Correlated Equilibrium as an Expression of Bayesian Rationality." <u>Econometrica</u> 55: 1-18.

Axelrod, R. (1980). "The Emergence of Cooperation among Egoists." <u>American Political Science Review</u> 75: 306-18.

Axelrod, R. (1984). <u>The Evolution of Cooperation</u>. New York, Basic Books.

Bagnoli, M. and M. McKee (1991). "Voluntary Contribution Games: Efficient Private Provision of Public Goods." <u>Economic Inquiry</u> 29: 351-66.

Banks, J., C. R. Plott, et al. (1988). "An Experimental Analysis of Unanimity in Public Goods Provision Mechanisms." <u>Review of economic studies</u> 55(182): 301-22.

Baumol, W. J. and W. E. Oates (1988). <u>The Theory of Environmental Policy</u>. New York, Cambridge University Press.

Becker, J. L. and R. Sarin (1987). "Gamble Dependent Utility." <u>Management Science</u> 33: 1367-82.

Bedsworth, L. W. and W. Kastenberg (2002). "Science and Uncertainty in Environmental Regulation: Insights from the Evaluation of California's Smog Check Program." Science and Public Policy 29(1): 13-24.

Ben-David, S., D. S. Brookshire, et al. (1999). "Heterogeneity, Irreversible Production Choices, and Efficiency in Emission Permit Markets." Journal of Environmental Economics and Management 38: 176-194.

Berk, R. A. (1990). A Primer on Robust Regression. Modern Methods of Data Analysis. J. Fox and J. S. Long. Newbury Park, CA, Sage Publications: 292-324.

Bohm, P. (1972). "Estimating Demand for Public Goods: An Experiment." European Economic Review 3: 111-30.

Bouyssou, D. and e. al.], Eds. (2002). Aiding Decisions with Multiple Criteria : Essays in Honor of Bernard Roy. Boston, Kluwer Academic Publishers.

Boyd, L. H. and G. R. Iversen (1979). Contextual Analysis: Concepts and Statistical Techniques. Belmont, CA, Wadsworth Publishing Company.

Bridgman, P. W. (1922). Dimensional Analysis. New Haven, CT, Yale University Press.

Brookshire, D. S., D. Coursey, et al. (1989a). "Special Interests and the Voluntary Provision of Public Goods." Discussion paper. Washington university, St. Louis.

Broseta, B. (2000). "Adaptive Learning and Equilibrium Selection in Experimental Coordination Games: An ARCH (1) Approach." Games and Economic Behavior 32: 25-50.

Brown, R. V., A. S. Kahr, et al. (1974). Decision Analysis for the Manager. New York, Holt, Rinehart, & Winston.

Brown-Kruse, J. and D. Hummels (1993). "Gender Effects in Laboratory Public Goods Contribution: Do Individuals Put Their Money Where Their Mouth Is?" Journal of Economic behavior and organization 22: 255-67.

Cadle and et-al. (1994). Journal of the Air and Waste Management Association 44.

Camerer (1995). Individual Decision Making. The Handbook of Experimental Economics. J. H. Kagel and A. E. Roth. Princeton, NJ, Princeton University Press: 587-703.

CARB (1985). "California I/M Program Evaluation." California Air Resources Board, MS-86-002.

CARB (2000). "Evaluation of California's Enhanced Vehicle Inspection and Maintenance Program (Smog Check Ii)." California Air Resources Board: 50.

Carnap, R. (1950). "Empiricism, Semantics, and Ontology." Revue Internationale De Philosophie IV: 20-40.

Carraro, C. and D. Siniscalo (1992). "Environmental Innovation Policy and International Competition." <u>Environmental and Resource Economics</u> 2: 183-200.

Carraro, C. and D. Siniscalo (1993). "Strategies for the International Protection of the Environment." <u>Journal of Public Economics</u> 52: 309-328.

Cason, T. and C. R. Plott (1996). "Epa's New Emissions Trading Mechanism: A Laboratory Evaluation." <u>Journal of Environmental Economics and Management</u> 30: 133-160.

Chamberlin, J. (1978). "The Logic of Collective Action: Some Experimental Results." <u>Behavioral science</u> 23: 441:5.

Chander, P. and H. Tulkens (1992). "Theoretical Foundations of Negotiations and Cost Sharing in Transfrontier Pollution Problems." <u>European Economic Review</u> 36: 288-299.

Chew, S. H. (1983). "A Generalization of the Quasilinear Mean with Applications to the Measurement of Income Inequality and Decision Theory Resolving the Allais Paradox." <u>Econometrica</u> 51: 1065-92.

Clarke, E. H. (1971). "Multipart Pricing of Public Goods." <u>Public choice</u> 11: 17-33.

Cleveland, H. (1973). "The Decision Makers." <u>The Center Magazine</u> 6(5): 9-18.

Cook, R. D. and S. Weisberg (1983). "Diagnostics for Heteroskedasticity in Regression." <u>Biometrika</u> 70: 1-10.

Cook, T. and D. T. Campbell (1979). <u>Quasi-Experimentation: Design & Analysis Issues for Field Settings</u>. Boston, Houghton Mifflin.

Corley, E., L. DeHart-Davis, et al. (2003). "Inspection/Maintenance Progam Evaluation: Replicating the Denver Step Method for an Atlanta Fleet." <u>Environmental Science and Technology</u> 37: 2801-2806.

Corner, J., J. Buchanan, et al. (2001). "Dynamic Decision Problem Structuring." <u>Journal of Multi-Criteria Decision Analysis</u> 10: 129-141.

Costanza, R., R. d'Arge, et al. (1997). "The Value of the World's Ecosystem Services and Natural Capital." <u>Nature</u> 387: 253.

Dawes, R. (1975). Formal Models of Dilemmas in Social Decision-Making. <u>Human Judgement and Decision Processes</u>. M. Kaplan and S. Schwartz. New York, Academic Press: 87-107.

Dawes, R. (1980). "Social Dilemmas." <u>Annual Review of Psychology</u> 31: 169-93.

Dawes, R., J. McTavish, et al. (1977). "Behavior, Communication, and Assumptions About Other People's Behavior in a Commons Dilemma Situation." Journal of Personality and social psychology 35(1): 1-11.

Dawes, R. and J. Orbell (1982). Cooperation in Social Dilemma Situations: Thinking About It Doesn't Help. Research in Experimental Economics. V. L. Smith. Greenwich, Conn., JAI press. 2.

Dawes, R., J. Orbell, et al. (1986). "Organizing Groups for Collective Action." American Political Science Review 80: 1171-85.

Dawes, R. and R. Thaler (1988). "Cooperation." Journal of economic perspectives 2(3): 187-97.

Dawes, R., A. van de Kragt, et al. (1987). "Not Me or Thee but We: The Importance of Group Identity in Eliciting Cooperation in Dilemma Situations: Experimental Manipulations." Presented at the Public choice meeting, Tucson, Arizona, March 28, 1987.

DeHart-Davis, L. (2000). Environmental Permit Application Costs : The Role of Red Tape, Subcontracting, Experience and Communications. Atlanta, Ph.D. thesis, School of Public Policy, Georgia Institute of Technology.

DeHart-Davis, L., E. Corley, et al. (2002). "Evaluating Vehicle Inspection/Maintenance Programs Using on-Road Emissions Data: The Atlanta Reference Method." Evaluation Review 26(2): 111-146.

Dekel, E. (1986). "An Axiomatic Characterization of Preferences under Uncertainty: Weakening the Independence Axiom." Journal of Economic Theory 40: 304-18.

Dunn, W. N. (1998). The Experimenting Society: Essays in Honor of Donald T. Campbell. Policy Studies Review Annual, Volume 11.

Dutta, A. (1996). "Integrating Ai and Optimization for Decision Support: A Survey." Decision Support Systems 18: 217-226.

Edwards, J., S. Walters, et al. (1994). "Hospistal Admissions for Asthma in Pre-School Children: Relationship to Major Roads in Birmingham Uk." Arch Enviro Health 49: 223-237.

Environ, I. (1998). "Performance Audit of the Colorado Air Program." 32.

EPA (1978). "Guidance for Vehicle Inspection/Maintenance Programs."

EPA (1993). Clean Cars for Clean Air: Inspection and Management Programs.

EPA (1994). Vehicle Fuels and the 1990 Clean Air Act.

EPA (1998). "Inspection and Maintenance (I/M) Program Effectiveness Methodologies."

EPA (2000). "National Air Pollutant Emission Trends, 1900-1998."

EPA (2002). "Guidance on Use of Remote Sensing for Evaluation of I/M Program Performance."

Franciosi, R., R. Isaac, et al. (1993). "An Experimental Investigation of the Hahn-Noll Revenue Neutral Auction for Emission Licenses." Journal of Environmental Economics and Management 24: 1-24.

Freeman, A. M. (1993). The Measurement of Environmental and Resource Values: Theory and Methods. Washington, D.C, Resources for the Future.

Friedman, M. S., K. E. Powell, et al. (2001). "Impact of Changes in Transportation and Commuting Behaviors During the 1996 Summer Olympic Games in Atlanta on Air Quality and Childhood Asthma." JAMA; Chicago; 285(7): 897-905.

Gal, T., T. J. Stewart, et al., Eds. (1999). Multicriteria Decision Making: Advances in Mcdm Models, Algorithms, Theory, and Applications. Boston, Kluwer Academic.

Gintis, H. (2000). "Beyond Homo-Oeconimcus: Evidence from Experimental Economics." Ecological Economics 35: 311-322.

Glover, E. and D. Brzezinski (1997). "Analysis of the Arizona Im240 Test Program and Comparison with the Tech5 Model."

Gray, W. B. and J. Scholz (1993). "Does Regulatory Enforcement Work? A Panel Analysis of Osha Enforcement." Law and Society Review 27: 177-213.

Greene, W. H. (2000). Econometric Analysis. Upper Saddle River, N.J., Prentice Hall.

Groves, T. (1973). "Incentives in Teams." Econometrica 41: 617-31.

Groves, T. and J. O. Ledyard (1977). "Optimal Allocation of Public Goods: A Solution to the "Free Rider" Problem." Econometrica 45: 783-809.

Gundersen, A. (1995). The Environmental Promise of Democratic Deliberation. Madison, Wisconsin, University of Wisconsin Press.

Gunderson, L. H. and C. S. Holling, Eds. (2002). Panarchy: Understanding Transformations in Human and Natural Systems,. Washington, Island Press.

Gunderson, L. H., C. S. Holling, et al. (1995). Barriers and Bridges to the Renewal of Ecosystems and Institutions. New York, Columbia University Press.

Gunningham, N., R. A. Kagan, et al. (2003). Shades of Green: Regulation, Business, Environment. Palo Alto, CA, Stanford University Press.

Habermas, J. (1998). Between Facts and Norms: Contributions to a Discourse Theory of Law and Democracy. Cambridge, Massachusetts, The MIT Press.

Haines, F. (1997). Corporate Regulation: Beyond "Punish or Persuade". Oxford, Clarendon Press.

Hall, A. D. (1989). Metasystems Methodology: A New Synthesis and Unification. Oxford, Pergamon Press.

Hanne, T. (2001). Intelligent Strategies for Meta Multiple Criteria Decision Making. Boston, Kluwer.

Hardin, G. (1968). "The Tragedy of the Commons." Science 162: 1243-1248.

Hardin, R. (1982). Collective Action. Baltimore, Md., Johns Hopkins University Press.

Harrington, W., V. McConnell, et al. (1999). "Coase and Car Repair: Who Should Be Responsible for Emissions
of Vehicles in Use?" Resources for the Future, Washington DC.

Harrington, W., V. McConnell, et al. (2000). "Are Vehicle Emission Inspection Programs Living up to Expectations?" Transportation Research Part D-Transport and Environment 5(3): 153-72.

Harrington, W., V. McConnell, et al. (1998). "A Behavioral Analysis of EPA's Mobile Emission Factor Model." Discussion paper 98-47, Resources for the Future.

Harrison, K. (1999). "Talking with the Donkey: Cooperative Approaches to Environmental Protection." Journal of Industrial Ecology 2: 51-72.

Harsanyi, J. C. (1995). "A New Theory of Equilibrium Selection for Games with Incomplete Information." Games and Economic Behavior 10: 318-332.

Helland, E. (1998). "The Enforcement of Pollution Control Laws: Inspections, Violations and Self-Reporting." The review of economics and statistics 80: 141-153.

Hershey, J. C. and P. Shoemaker (1980). "Prospect Theory's Reflection Hypothesis: A Critical Examination." Organizational behavior and human decision processes 25: 395-418.

Hershey, J. C. and P. Shoemaker (1985). "Probability Versus Certainty Equivalence Methods in Utility Measurement: Are They Equivalent?" Management Science 31: 1213-31.

Hobbs, B. F. (1980). "A Comparison of Weighting Methods in Power Plant Citing." Decision Sciences 11: 725-737.

Holling, C. S. (1978). Adaptive Environmental Assessment and Management. London, John Wiley.

Holling, C. S. (1992). "Cross-Scale Morphology, Geometry and Dynamics of Ecosystems." Ecological Monographs 62(4): 447-502.

Holloway, C. A. (1979). Decision Making under Uncertainty: Models and Choices. Englewood Cliffs, NJ, Prentice-Hall.

Hume, D. (1777/1955). An Inquiry Concerning Human Understanding: With a Supplement, an Abstract of a Treatise of Human Nature. Indianpolis, Bobbs-Merrill Educational Pub.

Hwang, C. and K. P. Yoon (1981). Multiple Attribute Decision Making: Methods and Applications. New York, Springer-Verlag.

Isaac, R., K. McCue, et al. (1985). "Public Goods Provision in an Experimental Environment." Journal of Public Economics 26: 51-74.

Isaac, R., D. Schmidtz, et al. (1988). "The Assurance Problem in a Laboratory Market." Public choice 62(3): 217-36.

Isaac, R. and J. M. Walker (1984). "The Effects of Communication on Free Riding Behavior." Discussion paper. University of Arizona, Tucson.

Isaac, R. and J. M. Walker (1989). "Complete Information and the Provision of Public Goods." Discussion paper 89-18, University of Arizona, Tucson.

Isaac, R. and J. M. Walker (1991). Costly Communication: An Experiment in a Nested Public Goods Problem. Laboratory Research in Political Economy. T. Palfrey. Ann Arbor, University of Michigan Press.

Isaac, R., J. M. Walker, et al. (1984). "Divergence Evidence on Free-Riding: An Experimental Examination of Possible Explanations." Public choice 43(1): 113-49.

Isaac, R., J. M. Walker, et al. (1990). "Group Size and the Voluntary Provision of Public Goods: Experimental Evidence Utilizing Very Large Groups." Working papers in economics, Indiana University.

Isaac, R. M. and J. M. Walker (1988a). "Communication and Free Riding Behavior: The Voluntary Contributions Mechanism." Economic Inquiry 26(2): 585-608.

Isaac, R. M. and J. M. Walker (1988b). "Group Size Effects in Public Goods Provision: The Voluntary Contributions Mechanism." Quarterly journal of economics 103: 179-99.

Kagel, J. H. and A. E. Roth, Eds. (1995). The Handbook of Experimental Economics,, Princeton University Press.

Kahneman and Tversky. (1988). <u>Risk and Rationality: Can Normative and Descriptive Analysis Be Reconciled?</u>

Kahneman, D. and A. Tversky (1979). "Prospect Theory: Analysis of Decision under Risk." <u>Econometrica</u> 47(2): 263-291.

Kahneman, D. and A. Tversky (1982). "The Psychology of Preferences." <u>Scientific American</u> 246(1): 160-173.

Kauffman, S. A. (1993). <u>The Origins of Order: Self Organization and Selection in Evolution</u>. New York, Oxford University Press.

Kauffman, S. A. (1995). <u>At Home in the Universe: The Search for the Laws of the Self Organization and Complexity</u>. New York, Oxford University Press.

Keeney, R. L. (1988). "Building Models of Values." <u>European Journal of Operational Research</u>.

Keeney, R. L. (1992). <u>Value Focused Thinking</u>. Harvard, MA., Harvard University Press.

Keeney, R. L. (1996). "Value-Focused Thinking: Identifying Decision Opportunities and Creating Alternatives." <u>European Journal of Operational Research</u> 92: 537-549.

Keeney, R. L. and H. Raiffa (1976). <u>Decisions with Multiple Objectives</u>. New York, Wiley.

Kim, O. and J. M. Walker (1984). "The Free Rider Problem: Experimental Evidence." <u>Public choice</u> 43: 3-24.

King, A. A. and M. J. Lenox (2000). "Industry Self-Regulation without Sanctions: The Chemical Industry's Responsible Care Programs." <u>Academy of Management Journal</u> 43: 698-716.

King, G. (1997). <u>A Solution to the Ecological Inference Problem: Reconstructing Individual Behavior from Aggregate Data</u>. Princeton, NJ, Princeton University Press.

Klausmeier, R. and Weyn (1997). "Using Remote Sensing Devices to Evaluate the California Smog Check Program." <u>Report to the California Bureau of Automotive Repair.</u>

Kuperan, K. and J. G. Sutinen (1998). "Blue Water Crime: Deterrence, Legitimacy, and Compliance in Fisheries." <u>Law and Society Review</u> 32: 309-330.

Lawson, D. R. (1993). ""Passing the Test"-- Human Behavior and California's Smog Check Program." <u>Journal of the Air and Waste Management Association</u> 43(December): 1567-75.

Lawson, D. R. (1995). "The Costs of "M" in I/M--Reflections on Inspection/Maintenance Programs." Journal of the Air and Waste Management Association 45(6): 465-476.

Lawson, D. R., P. J. Groblicki, et al. (1990). "Emissions from in-Use Motor Vehicles in Los Angeles: A Pilot Study of Remote Sensing and the Inspection and Maintenance Program." Journal of the Air and Waste Management Association 40(8): 1096-1105.

Ledyard, J. O. (1995). Public Goods: A Survey of Experimental Research. The Handbook of Experimental Economics. J. H. Kagel and A. E. Roth. Princeton, NJ, Princeton University Press.

Lee, K. N. (1993). Compass and Gyroscope: Integrating Science and Politics for the Environment. Washington, D.C, Island Press.

Lehmann, M. A. (2000). Negotiating Environmental Quality: Policy Implementation in Germany and the United States. Cheltenham, UK, Edward Elgar.

Lindahl, E. (1919/1958). Die Gerechtigkeit Der Besteurung. [English: Just Taxation-a Positive Solution]. Classics in the Theory of Public Finance. R. A. Musgrave and A. T. Peacock. London, Macmillan.

Livingstone, A. E., G. Shaddick, et al. (1996). "Do People Living near Inner City Main Roads Have More Asthma Needing Treatment? Case-Control Study." BMJ 312: 676-677.

Loomes, G., C. Starmer, et al. (1991). "Observing Violations of Transitivity by Experimental Methods." Econometrica 59: 17-33.

MacCrimmon, K. R. (1965). An Experimental Study of the Decision Making Behavior of Business Executives, Unpublished dissertation. University of California, Los Angeles.

Machina, M. J. (1982). ""Expected Utility" Analysis without the Independence Axiom." Econometrica 50: 277-323.

Marwell, G. (1982). Altruism and the Problem of Collective Action. Cooperation and Helping Behavior: Theories and Research. V. Derlega and J. Grzelak. New York, Academic Press.

Marwell, G. and R. Ames (1979). "Experiments on the Provision of Public Goods I: Resources, Interest, Group Size, and the Free-Rider Problem." American Journal of Sociology 84(6): 1335-60.

Marwell, G. and R. Ames (1980). "Experiments on the Provision of Public Goods Ii: Provision Points, Stakes, Experience, and the Free-Rider Problem." American Journal of Sociology 85(4): 926-37.

Marwell, G. and R. Ames (1981). "Economists Free Ride, Does Anyone Else? Experiments on the Provision of Public Goods, Iv." Journal of Public Economics 15: 295-310.

Mas-Colell, A., M. D. Whinston, et al. (1995). Microeconomic Theory. New York, Oxford University Press.

Mason, C. F., O. R. Phillips, et al. (1991). "The Role of Gender in a Non-Cooperative Game." Journal of Economic behavior and organization 15: 215-35.

May, P. J. (2003). "Regulatory Compliance: Perspectives of Farmers, Homebuilders, and Marine Facilities." Paper presented at the 25th annual research conference of the Association for Public Policy Analysis and Management. Washington DC, November 6-8, 2003.

Maynard Smith, J. (1982). Evolution and the Theory of Games. New York, Cambridge University Press.

McClintock, P. (1999). "I/M Impact on Dayton Registration Transactions." Memorandum to P. Lorang and L. Platte, EPA OMS, from P. McClintock, Applied Analysis. July 5, 1999.

Meyer, B. D. (1995). "Natural and Quasi-Experiments in Economics." Journal of Business and Economic Statistics 13:151-161

Morrison, D. G. (1967). "On the Consistency of Preferences in Allais' Paradox." Behavioral science 12: 373-83.

Mount, K. and S. Reiter (1974). "The Informational Size of Message Spaces." Journal of Economic Theory 8: 161-91.

Norton, B. (1996). Integration or Reduction: Two Approaches to Environmental Values. Environmental Pragmatism. A. Light and E. Katz, Routledge: 105-138.

Norton, B. (1997). "Ecology and Opportunity: Intergenerational Equity and Sustainable Options."

Norton, B., R. Costanza, et al. (1998). "The Evolution of Preferences: Why Sovereign Preferences May Not Lead to Sustainable Policies and What to Do About It." Ecological Economics 24: 193-211.

Norton, B. G. (1977). "On the Metatheoretical Nature of Carnap's Philosophy." Philosophy of Science 44(1): 65-85.

Norton, B. G. (1991). "Thoreau's Insect Analogies: Or, Why Environmentalists Hate Mainstream Economists." Environmental Ethics 13: 235-261.

Norton, B. G. (1994). "Economists Preferences and the Preferences of Economists." Environmental Values 3: 311-332.

Norton, B. G. (1999). "Pragmatism, Adaptive Management, and Sustainability." Environmental Values 8: 451-466.

Norton, B. G. (in preparation). Constructing Sustainability: A Philosophy of Adaptive Ecosystem Management.

Norton, B. G. and A. Steinemann (2001). "Environmental Values and Adaptive Management,." Environmental Values 10(4): 473-506.

Norton, B. G. and M. Toman (1997). "Sustainability: Ecological and Economic Perspectives." Land Economics 73(4): 553-568.

NRC (2001). Evaluating Vehicle Inspection and Maintenance Programs: National Research Council. Washington DC, National Academy Press.

Orbell, J. and R. Dawes (1981). Social Dilemmas. Progress in Applied Social Psychology, Vol. 1. New York, John Wiley and sons: 117-33.

Orbell, J. and R. Dawes (1991). "A 'Cognitive Miser' Theory of Cooperators' Advantage." American Political Science Review 85: 515-28.

Orbell, J. and R. Dawes (1993). "Social Welfare, Cooperators' Advantage, and the Option of Not Playing the Game." American Sociological Review 58: 787-800.

Orbell, J., R. Dawes, et al. (1990). "The Limits of Multilateral Promising." ethics 100: 616-27.

Orbell, J., P. Schwartz-Shea, et al. (1992). "Gender as a Basis for Choosing Partners in Prisoners' Dilemma Games." Technical report, University of Oregon. Presented at the American Political Science Association Annual meeting in Chicago, 1992.

Orbell, J., P. Schwartz-Shea, et al. (1984). "Do Cooperators Exit More Readily Than Defectors." American Political Science Review 78(1): 147-62.

Orbell, J., A. van de Kragt, et al. (1988). "Explaining Discussion-Induced Cooperation." Journal of Personality and social psychology 54: 811-19.

Ostrom, E. (1990). Governing the Commons: The Evolution of Institutions for Collective Action. Cambridge, MA, Cambridge University Press.

Ostrom, E. (1999). "Coping with Tragedies of the Commons." Annual Review of Political Science 2: 493-535.

Ostrom, E. (2000). "Collective Action and the Evolution of Social Norms." Journal of Economic Perspectives 14(3): 137-158.

Ostrom, E. and J. M. Walker (1991). Communication in a Commons: Cooperation without External Enforcement. <u>Laboratory Research in Political Economy</u>. T. Palfrey. Ann Arbor, University of Michigan Press: 287-322.

Palfrey, T. and J. Prisbrey (1993). "Anomalous Behavior in Linear Public Goods Experiments: How Much and Why?" <u>Social Science working paper 833, California Institute of Technology</u>.

Palfrey, T. and H. Rosenthal (1991a). Testing Game Theoretic Models of Free-Riding: New Evidence on Probability Bias and Learning. <u>Laboratory Research in Political Economy</u>. T. Palfrey. Ann Arbor, University of Michigan Press.

Palfrey, T. and H. Rosenthal (1991b). "Testing for Effects of Cheap Talk in a Public Goods Game with Private Information." <u>Games and economic behavior</u> 3: 183-220.

Payne, J. W. (1976). "Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis." <u>Organizational behavior and human performance</u> 22: 17-44.

Petrosjan, L. A. and V. V. Mazalov (2000). <u>Game Theory and Applications V</u>. New York, Nova Science Publishers.

Pierson, W. R. (1996). "Motor Vehicle Inspection and Maintenance Programs- How Effective Are They?" <u>Atmospheric Environment</u> 30(21): i-iii.

Pokharel, S. S., G. A. Bishop, et al. (2000). On-Road Remote Sensing of Automobile Emissions in the Chicago Area: Year 3.

Poppe, M. and L. Utens (1986). "Effects of Greed and Fear of Being Gypped in a Social Dilemma Situation with Changing Pool Size." <u>Journal of Economic Psychology</u> 7: 61-73.

Prakash, A. (2000). <u>Greening the Firm</u>. Cambridge, UK, Cambridge University Press.

Quiggin, J. (1982). "A Theory of Anticipated Utility." <u>Journal of Economic behavior and organization</u> 3: 323-43.

Raiffa, H. (1968). <u>Decision Analysis</u>. Reading, MA, Addison-Wesley.

Rapoport, A. (1989). <u>Decision Theory and Decision Behavior: Normative and Descriptive Approaches</u>. Dordrecht, Kluwer Academic Publishers.

Rapoport, A. and R. Suleiman (1993). "Incremental Contribution in Step-Level Public Goods Games with Asymmetric Players." <u>Organizational behavior and human decision processes</u> 55: 171-94.

Rawls, J. (1971). <u>A Theory of Justice</u>. Cambridge, Mass., Belknap Press of Harvard University Press.

Riley, M. W. (1964). Sources and Types of Sociological Data. <u>Handbook of Modern Sociology</u>. R. Farris. Chicago, Rand McNally: 1015-21.

Rodgers, M., L. DeHart-Davis, et al. (under review). "Measuring Inspection/Maintenance Program Effectiveness Using Optical Remote Sensing: Results of the Continuous Atlanta Fleet Evaluation." <u>Submitted to Atmospheric Environment, November 1999.</u>

Rossi, P. H., Freeman, H. E. (1993). <u>Evaluation: a Systematic Approach</u>. Newbury Park, CA, Sage.

Rothman, E. D. (1998). "Assessment of the Report "Development of a Proposed Procedure for Determining the Equivalency of Alternative Inspection and Maintenance Programs"." <u>Center for statistical consultation and research, University of Michigan</u>.

Roy, B. (1971). "Problems and Methods with Multiple Objective Functions." <u>Mathematical Programming</u> 1: 239-266.

Saaty, T. L. (1980). <u>The Analytical Hierarchical Process</u>. New York, Wiley.

Scharpf, F. W. (1997). <u>Games Real Actors Play: Actor Centered Institutionalism in Policy Research</u>. Colorado, Westview Press.

Scherrer, H. C. and D. B. Kittelson (1994). "I/M Effectiveness as Directly Measured by Ambient Co Data." <u>Society of Automotive Engineers, Warrendale, PA</u>.

Schmidtz, D. (1991). <u>The Limits of Government: An Essay on the Public Goods Argument</u>. Boulder, Westview.

Schmidtz, D. (1993). "Reasons for Altruism." <u>Social philosophy and policy</u> 10: 52-68.

Segal, U. (1989). "Anticipated Utility: A Measure Representation Approach." <u>Annals of operations research</u> 19: 359-73.

Segerson, K. and T. J. Miceli (1998). "Voluntary Environmental Agreements: Good or Bad News for Environmental Protection." <u>Journal of Environmental Economics and Management</u> 36: 109-130.

Sell, J. and R. K. Wilson (1990). "The Effects of Signalling on the Provisioning of Public Goods." <u>Discussion paper, Workshop in Political Theory and Policy Analysis, Indiana University</u>.

Sen, A. (1999). "The Possibility of Social Choice." <u>American Economic Review</u> 89: 349-379.

Sierra-Research (1997). "Development of a Proposed Procedure for Determining the Equivalency of Alternative Inspection and Maintenance Programs." Sierra Research Inc., Sacramento, CA.

Sierra-Research (1998). "Review of Air Quality and Motor Vehicle Technology Issues Pertaining to the Design of Aircare Ii." Tech. Rept. no. SR98-07-01, Sacramento, CA.: 109.

Simon, H. A. (1960). The New Science of Management Decisions. New York, Harper and Row.

Simon, H. A. (1977). The Logic of Heuristic Decision Making. Models of Discovery: And Other Topics in the Methods of Science. R. S. a. M. W. W. Cohen. Boston, Reidel: 154-178.

Simon, H. A. (1982). Models of Bounded Rationality. Cambridge, MA, MIT Press.

Slott, R. S. (2002). Remote Sensing Measurement of Real World Vehicle High-Exhaust Emitters. Alpharetta, GA, Coordinating Research Council, Inc.

Slovic, P. (1995). "The Construction of Preference." American Psychologist 50: 364-371.

Slovic, P. and S. Lichtenstein (1968). "The Relative Importance of Probabilities and Payoffs in Risk Taking." Journal of Experimental Psychology 78: 208-17.

Slovic, P. and A. Tversky (1974). "Who Accepts Savage's Axiom?" Behavioral science 19: 368-73.

Starr, M. K. (1972). Production Management. Englewood Cliffs, NJ, Prentice-Hall.

Stedman, D. (1989). "Automobile Carbon Monoxide Emission." Environmental Science and Technology 23(2): 147-8.

Stedman, D., G. A. Bishop, et al. (1994). "On-Road Remote Sensing of Co and Hc Emissions in California." Final report to California Air Resources Board.

Stedman, D., G. A. Bishop, et al. (1997). "On-Road Evaluation of an Automobile Emission Test Program." Environmental Science & Technology 31(3): 927-31.

Stedman, D. H., G. A. Bishop, et al. (1997). "On-Road Evaluation of an Automobile Emission Test Program." Environmental Science & Technology 31: 927-31.

Stedman, D. H., G. A. Bishop, et al. (1998). "Repair Avoidance and Evaluating Inspection and Maintenance Programs." Environmental Science & Technology 32(10): 1544-45.

Stokes, D. E. (1969). Ecological Regression as a Game with Nature. Mathematical Applications in Political Science. J. L. Bernd. Charlottesville, University Press of Virginia.

Stone, D. (1997). Policy Paradox: The Art of Political Decision Making. New York, W.W.Norton & Company.

Suleiman, R. and A. Rapoport (1992). "Provision of Step-Level Public Goods with Continuous Contribution." Journal of Behavioral Decision Making 5: 133-53.

Tversky, A. (1969). "Intransitivity of Preferences." Psychological Review 76: 31-48.

Tversky, A. (1972). "Elimination by Aspects: A Theory of Choice." Psychological Review 79(4): 281-299.

von Neumann, J. and O. Morgenstern (1944). Theory of Games and Economic Behavior. Princeton, Princeton University Press.

Voogd, H. (1983). Multicriteria Evaluation for Urban and Regional Planning. London, Pion.

Walker, J. M. (1978). "A Note on the Characterization of Mechanisms for the Revelation of Preferences." Econometrica 46: 147-52.

Walker, J. M. (1980). "A Simple Incentive Compatible Scheme for Attaining Lindahl Allocations." Econometrica 46: 1521-40.

Walker, J. M., R. Gardner, et al. (1990). "Rent Dissipation in Limited Access Common Pool Resource Environments: Experimental Evidence." Journal of Environmental Economics and Management 19: 203-11.

Walters, C. J. (1986). Adaptive Management of Renewable Resources. New York, MacMillan.

Weiss, C. H. and M. J. Bucuvalas (1980). Social Science Research and Decision-Making. NY, Columbia University Press.

Welch, E. W., A. Mazur, et al. (2000). "Voluntary Behavior by Electric Utilities: Levels of Adoption and Contribution of the Climate Challenge Program to the Reduction of Carbon Dioxide." Journal of Policy Analysis and Management 19: 407-425.

Wenzel, T. (1997). I/M Failure Rates by Vehicle Model. 7th CRC on-road vehicle emissions workshop, San Diego, CA.

Wenzel, T. (1999a). "Using Program Test Data to Evaluate the Phoenix I/M Program: Report to the Arizona Department of Environmental Quality." Lawrence Berkeley National Laboratory: 4.

Wenzel, T. (1999b). "Evaluation of Arizona's Enhanced I/M Program." Presentation at the Ninth Road Vehicle Emissions Workshop, San Diego, CA.

Wenzel, T. (2003). "Use of Remote Sensing Measurements to Evaluate Vehicle Emission Monitoring Programs: Results from Phoenix, Arizona." <u>Environmental Science & Policy</u> 6: 153-166.

Wenzel, T., E. Gumerman, et al. (2000b). "Evaluation of the Enhanced Smog Check Program: A Report to the California Inspection and Maintenance Review Committee." Pp. 140.

Wenzel, T. and R. Sawyer (1998a). "Review of Sierra Research Report "Development of a Proposed Procedure for Determining the Equivalency of Alternative Inspection and Maintenance Programs"." <u>Lawrence Berkley National Laboratory, Berkley, CA</u>.

Wenzel, T., B. C. Singer, et al. (2000a). "Some Issues in the Statistical Analysis of Vehicle Emissions." <u>Journal of Transportation Statistics</u> 3(2): 1-14.

White, H. (1980). "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." <u>Econometrica</u> 48: 817-838.

Winterfeldt, D. V. and W. Edwards (1986). <u>Decision Analysis and Behavioral Research</u>. New York, Cambridge University Press.

Wjst, M., P. Reitmeir, et al. (1993). "Road Traffic and Adverse Effects on Respiratory Health in Children." <u>BMJ</u> 307: 596-600.

Xepapadeas, A. (1997). <u>Advanced Principles in Environmental Policy</u>. Northampton, MA, Edward Elgar.

Yoon, K. P. (1989). "The Propogation of Errors in Multiple-Attribute Decision Analysis: A Practical Approach." <u>Journal of Operational Research Society</u> 40: 681-686.

Yu, P. L. (1979). "Second-Order Game Problem: Decision Dynamics in Gaming Phenomena." <u>Journal of Optimization Theory and Applications</u> 27: 147-166.

Yu, P. L. (1985). <u>Multiple-Criteria Decision Making: Concepts, Techniques, and Extensions</u>. New York, NY, Plenum.

Zadeh, L. A. (1965). "Fuzzy Sets." <u>Information and Control</u> 8: 338-353.

Zadeh, L. A. (1968). "Probability Measures of Fuzzy Events." <u>Journal of Mathematical analysis and applications</u> 23: 421-27.

Zadeh, L. A. (1973). "Outline of a New Approach to the Analysis of Complex System and Decision Processes." <u>IEEE Transactions on Systems, Man and Cybernetics</u> SMC-3,: 28-44.

Zadeh, L. A. (1986). "A Simple View of the Dempster_Shafer Theory of Evidence and Its Implications for the Rule of Combination of Evidence." <u>AI Magazine</u> 7: 85-90.

Zadeh, L. A. (1995). "Discussion: Probability Theory and Fuzzy Logic Are Complementary Rather Than Competitive." <u>Technometrics</u> 37: 271-6.

Zeleny, M. (1982). <u>Multiple Crietia Decision Making</u>. New York, McGraw-Hill.

Zhang, Y., D. H. Stedman, et al. (1993). "On-Road Hydrocarbon Remote Sensing in the Denver Area." <u>Environmental Science & Technology</u> 27(9): 1885-1891.