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An Empirical Study of Alternative Fuel Vehicle Choice by Commercial Fleets: Lessons in Transportation Choices, and Public Agencies' Organization

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An Empirical Study of Alternative Fuel Vehicle Choice by Commercial Fleets: Lessons in Transportation Choices, Cost Efficiency, and Public Agencies' Organization

DISSERTATION

submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in Economics

by

Soheila Soltani Crane

Dissertation Committee:
Professor David Brownstone, Co-Chair
Professor Linda Cohen, Co-Chair
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1996

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1996

Dedicated

to

my father, my mother,

Jack,

Parisa, and Roxana.

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"The Demand for Alternative Fuel Vehicles by California Commercial Fleets," Graduate Research Paper, UC Irvine, 1995.

"Precursors of Demand for Alternative-Fuel Vehicles: Results from a Survey of 2,000 Fleet Sites in California," with Thomas Golob and Jane Torous, Working Paper UCI-ITS-WP-94-8, UC Irvine, 1994.

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ABSTRACT OF THE DISSERTATION

An Empirical Study of Alternative Fuel Vehicle Choice by Commercial Fleets: Lessons in Transportation Choices, Cost Efficiency, and Public Agencies' Organization

by Soheila Soltani Crane

Doctor of Philosophy in Economics

University of California, Irvine, 1996

Professors David Brownstone and Linda Cohen, Co-Chairs.

The concern about air pollution has led government agencies to design and implement mandates to replace some commercial fleets' gasoline vehicles with Alternative Fuel Vehicles (AFVs). In Part One of this dissertation, I investigate the diffusion of AFVs in the commercial sector. Commercial fleets are frequently the first target of government regulation because policy agencies can target a large number of vehicles while regulating fewer establishments relative to the household sector. Using stated preference survey data from over 2000 commercial and local government fleets in California, I estimate multinomial logit and nested logit models of fuel choice that predict the probability of choosing each type of AFV. Given certain assumptions about vehicle technology, these models predict that starting in year 2010, almost 17% of new vehicle purchases by the commercial and local government fleets will be electric, about 20% will be compressed natural gas, and almost 21% will be methanol vehicles.

I find that fuel choice probabilities differ depending on the market structure. Public agencies seem to be more AFV friendly than private firms. Important factors in fleet vehicle choice are the degree of familiarity of the firm's staff with the AFV operation, the size of the establishment, government regulations, and the availability of the refueling infrastructure.

In Part Two, I review hypotheses about the determinants of local government agencies' efficiency and use the stated preference survey data to test these hypotheses. Public choice models predict systematic differences among government agencies regarding their cost considerations and sensitivity to environmental issues. The empirical evidence identifies two factors that affect government agencies' performance. The first factor is jurisdiction: an agency that has a more rigid boundary, such as a city or a county, seems to operate more efficiently than an agency that has more flexible geographic boundaries, as is the case with the special districts. The second factor is direct citizen voting: an agency director who is subject to re-election seems to coordinate a more efficient agency operation than one that is appointed to the job as a career position.

CHAPTER 1

OVERVIEW

This dissertation is divided into two distinct parts. In Part One, I develop models of fuel choice by commercial fleets and forecast the Alternative Fuel Vehicle (AFV) choice probabilities of commercial fleets in California. In Part Two, I develop theories about local government agencies' efficiency and use local government fleets data of alternative fuel choice to test these hypotheses.

The concern about air pollution has led government agencies to design and implement mandates to replace some commercial fleets' gasoline vehicles with AFVs. In Part One of this dissertation, I investigate the diffusion of AFVs in the commercial sector. I focus on commercial fleets because policy agencies can target large groups of vehicles with reduced volume of choices. The success of these policies, however, depends in part on the response of businesses to the new technologies: How would commercial fleets respond to the introduction of both a new wave of AFVs and the AFV mandates? How does a firm decide whether or not to purchase an AFV? Which types of firms are the most likely first adopters of AFVs? How does the diffusion rate of AFVs vary across different segments of the market? Why are there differences in the rate of AFV diffusion among various groups of fleet owners?

I estimate fuel choice models that predict the probability of choosing each type of AFV in the next fifteen years. These models predict the probability that an AFV would be chosen by different types of firms or local government agencies. More importantly, these models forecast how these probabilities change when technology assumptions are altered: What if we could not make electric vehicles with 150 miles vehicle range? What if we could make compressed natural gas (CNG) vehicles with over 300 miles vehicle range? What if we could improve on the refueling time or refueling cost of CNG vehicles? My fuel choice models address these types of questions.

The results could also assist policy makers in formulating their guidelines: What if we did not have a zero-emission mandate? What if we offered incentives for people to purchase electric or CNG vehicles? What if we invested in electric vehicle recharging infrastructure? What if we imposed gasoline taxes to pay for environmental damages?

Part One is organized as follows: In Chapter 2, I describe the air pollution problem, the proposed solutions, and explain why it is imperative to study the diffusion of alternative fuel vehicles in the commercial sector. I also inventory the main issues that this dissertation addresses and present an overview of the previous research.

Chapter 3 describes the data and survey instrument, and explains in detail the *stated preference* scenarios that were used to gather vehicle choice data. Furthermore, I provide some descriptive statistics on the sampled fleets. These include industry segmentation breakdowns as well as vehicle and firm characteristics. This chapter provides some background information about the type of firms that were included in the study along with a snap shot of their vehicle fleets' characteristics.

Chapter 4 presents the theoretical framework for my fuel choice models. I explain why I chose the utility maximization models, and why I model the fleet managers' utility maximizing choices. Both multinomial conditional logit models and nested logit models are briefly explained. Furthermore, I provide some model specification tests to test different models against each other.

In Chapter 5, I estimate the fuel choice models with the data from the survey of fleets in California, and analyze and interpret these results. Finally, I forecast the demand for AFVs by fleet owners given certain vehicle technology assumptions. I predict that starting in year 2010, almost 17% of new vehicle purchases will be electric, about 20% will be compressed natural gas, and almost 21% will be methanol vehicles. This predicted market shares for AFVs are higher than the predictions for the household vehicle market, as expected.

Chapter 6 concludes Part One of this dissertation by extending the fuel choice models across different market segments. I classify the firms in my study by market segments based on the degree by which they are regulated. I find that fuel choice probabilities differ depending on the market structure. Public agencies seem to be more AFV friendly than private firms. An important factor in fleet vehicle choice is the degree of familiarity of the firm's staff with the AFV operation. Government regulations seem to affect AFV choice greatly, and so does the availability of the refueling infrastructure. These findings are important for both policy design and marketing purposes.

Part Two deals with the public choice issues that might affect purchasing choices of government agencies. In Chapter 7, I analyze the underlying reasons why public organizations might respond differently to AFVs than private organizations and why I expect to find variations in both cost considerations and sensitivity to the environmental issues within public organizations. I first review the previous literature regarding public agency organizations. Then, I formulate some hypotheses about purchasing decisions of organizations that differ as to their geographical and structural makeup. I use the fuel choice survey and estimate fuel choice models to examine the cost consciousness of public agencies. Consequently, I use these models to test hypotheses regarding different types of government agencies. The resulting evidence implies that two factors may affect government agencies' efficient performance. The first factor is geographic constraint: an agency that has a more rigid boundary, such as a city or a county, seems to operate more efficiently than an agency that has more flexible geographic boundaries, as is the case with the special districts. The second factor is direct citizen voting: an agency director who is subject to re-election seems to coordinate a more efficient agency operation than one that is appointed to the job as a career position.

PART ONE

MODELS OF ALTERNATIVE FUEL VEHICLE CHOICE

BY COMMERCIAL FLEETS

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

2.1 The Problem

Our sophisticated transportation systems have improved accessibility, but they have also contributed to air pollution. Emissions of carbon monoxide, nitrogen oxides, volatile organic compounds, particulate matters, and other pollutants caused by transportation sources threaten public health. Although emission levels have gone down in the last decade, they remain dangerously high.[1] Emissions of over sixty percent of the carbon monoxide, thirty percent of the nitrogen oxides , and twenty six percent of the volatile organic compounds were attributed to highway vehicles in 1993 in the U.S.[2] Small and Kazimi (1995) estimate the health related cost of gasoline automobile emissions in Los Angeles area to be 3.4 cents per vehicle-mile driven, which translates to an annual cost of $442[3] per vehicle.

Highway vehicles' emissions could be reduced either by reducing the quantity of vehicle-miles driven, or by reducing the amount of tailpipe emissions per vehicle-mile. Trip management programs such as those encouraging carpooling and the construction of High Occupancy Vehicle (HOV) lanes are attempts to reach the former objective. The

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[1] See South Coast Air Quality Management District's "1994 Air Quality Management Plan", September 1994, pp. ES-4.
[2] See Davis, 1995.
[3] Assuming 13,000 average annual vehicle-mile traveled (VMT) for automobiles. (Source: Davis, 1995, Table 1.8)

effectiveness of trip management programs in reducing air pollution, however, has been questioned. Small and Kazimi (1995) study the cost of air pollution caused by motor vehicles. They find that “[c]hanges to both vehicles and fuel can offer substantial aggregate cost savings. But our findings do not provide much support for policies to reduce motor vehicle use overall.”

The amount of emission per vehicle-mile can be reduced by replacing current vehicles with vehicles that burn less fuel per mile, or with vehicles that produce less emissions by using catalytic converters, fuel injection technology, or alternative fuel vehicles. Fuel economy regulation has forced the automobile manufacturers to produce more fuel efficient vehicles. Higher gasoline prices in the late seventies and early eighties encouraged some consumers to seek fuel efficient gasoline vehicles as a way of reducing the cost of gasoline refueling. Fuel economy programs, however, have been thought to be marginally effective, if at all, with regard to the air pollution. Some studies have even claimed that fuel economy programs have had an adverse affect on the air pollution because of the way per vehicle emissions have been regulated. (Khazzom, 1988; Khazzom and Shelby, 1990)

Regulators have attempted to reduce emission per vehicle-mile by setting a low emission limit per vehicle. Emission ceilings have continuously been lowered in the last two decades and the Clean Air Act Amendment of 1990 has lowered them further. California has been in the forefront of tough emission standards and is continuing this tradition by setting emission restrictions below Federal standards. For example, a zero-emission mandate is proposed by the California Air Resources Board (CARB) which requires at least 10% zero emission vehicle (ZEV) sales in California starting in year 2003[4]. Similar mandates have been and are likely to be proposed which would require some mandatory replacement of the conventional gasoline vehicles with alternative fuel vehicles such as electric vehicles, natural gas vehicles, or vehicles that run on alcohol-based fuels such as methanol.

Alternative fuel vehicles have also become important because of energy concerns. The U.S. has become increasingly dependent on imported petroleum to fill domestic consumption needs. In 1993 imported oil and petroleum products accounted for nearly 50% of U.S. petroleum consumption.[5] The current political instability of major producers of imported petroleum leads to supply and price uncertainties. These uncertainties may be magnified in the next decades as the easy-access supply of petroleum diminishes. Deeper extraction levels of oil lead to higher cost of extraction and thus higher gasoline prices. Vehicles run on electricity, hence, may look more attractive in the presence of increasing gasoline prices.

Government policies such as those described above have brought alternative fuel vehicles (AFVs) into the spotlight. Vehicle manufacturers claim that the technological limitations of AFVs would make them unmarketable. Regulators, on the other hand, insist that an initial forced adoption of some AFVs would make way for mass production and diffusion of AFVs and thus relieve air pollution problem as well as contribute to energy security.

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[4] This is the 1996 revised version of the California's Zero Emission Mandate. The phase-in plan of requiring 2% ZEV starting in 1998 and 5% ZEV starting in 2001, have been dropped. The 10% ZEV requirement starting in 2003 is still in place.

For both air pollution and energy reasons, alternative fuel vehicles have become an important component of environmental strategies. An AFV technology such as electric vehicles would alleviate both air pollution and energy security concerns because: (1) electric vehicles emit virtually no carbon monoxide, (2) electricity needed to run electric vehicles could be generated with generators that are less polluting, at least in concentrated urban areas, and (3) electricity generators could be run on non-petroleum sources. CNG and alcohol-based fuels also could be generated independent of petroleum sources. Furthermore, they are generally less polluting than gasoline vehicles. Thus, regulators have been devising policies to encourage the conversion of more gasoline vehicles to AFVs. But, devising a policy and attaining an actual level of adoption necessary to have a positive impact on the air pollution are two different issues. Studies are needed to determine the extent of a likely adoption of electric vehicles and other alternative fuel vehicles. This study addresses these issues.

2.2 Why Study Commercial Fleets

There are three relevant groups of vehicle consumers: households, commercial entities, and government entities. These groups select from three major types of vehicles: (a) automobiles, (b) light-duty trucks, and (c) heavy-duty trucks. The highest level polluting vehicles (per vehicle-mile) are heavy-duty trucks. According to Small and Kazimi (1995), heavy-duty diesel trucks cause a 53 cents per vehicle-mile cost to the public health in the

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[5] Source: Davis, 1995.

Los Angeles Basin area, compared to the health cost of automobiles which is estimated at 3.4 cents per vehicle-mile for 1992. Heavy-duty trucks' vehicle-miles traveled (VMT) has increased faster than personal vehicles' VMT in the past years[6] and heavy-duty trucks' fuel economy is substantially lower than light duty vehicles (about 7 miles per gallon in 1987 compared to over 20 miles per gallon for personal vehicles). This could translate into higher fuel consumption and thus higher emissions from heavy-duty trucks per vehicle-mile compared to the other types of vehicles. In fact, emissions of nitrogen oxides (NO_x) from heavy-duty vehicles constitute 32% of NO_x emission in 1980 and 36% of NO_x emission in 1990 by all transportation sources.[7]

Thus, it seems logical to target heavy-duty vehicles in emission reduction programs. Heavy-duty trucks, however, are not regulated as much as other types of vehicles. California Air Resources Board's restrictive AFV emissions schedules do not apply to heavy-duty trucks. One reason could be that the trucking industry is a strong lobbying group with much political power to shield itself from cost inducing regulation. Another reason could be that alternative fuel vehicle technology is not mature enough to meet the demands of heavy trucks with high daily VMT.

Among light-duty vehicle users, the household vehicle group is probably the group that contributes more emissions on aggregate than commercial fleets. Household vehicles constitute a substantially larger portion of the vehicle population - the personal vehicle stock

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[6] Source: Davis, 1995.
[7] Source: U.S. Environmental Protection Agency, National Air Pollutant Emission Estimates, 1900-1993, 1994, p. A8.

of automobiles in the U.S. is reported at over 113 million while similar vehicles in fleets of 10 or more are estimated to be about 7.6 million vehicles[8]. The household vehicle stock is older and thus more polluting than commercial vehicle stock (shown in Figure 1 by skewness of the vintage/ vehicle count distribution of household vehicles compared to fleet vehicles). However, households drive their vehicles less than fleets do. In 1992, household average vehicle miles traveled (VMT) was 13,031[9] while commercial fleets' average VMT was at least twice that[10].

Even though the overall emission contribution from household vehicles may be larger than commercial fleets, it may be more practical to target commercial fleets as the first to use AFVs. There are several reasons. First, fleets have multiple vehicles and can rotate the vehicles for specific duties. They have more flexibility in choosing vehicle composition and range limits. Second, fleets have on-site refueling capabilities. They do not depend on outside refueling stations as much as households do. Third, fleets have more expertise with vehicle usage and maintenance than average households do. They could operate unfamiliar technology easier than households could. Fourth, it might be politically easier to mandate commercial entities to absorb social costs of air pollution than it is to mandate households. Finally, it is easier to monitor commercial fleets than households for regulations compliance

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[8] Note that commercial fleets' vehicles here do not include trucks.
Source: Davis, 1995. (ORNL-6856. Edition 15 of ORNL-5198) Table 3.3.

[9] Source: International Energy Studies, Energy Analysis Program, Lawrence Berkeley Laboratory, Berkeley, CA 1994. See Appendix C.

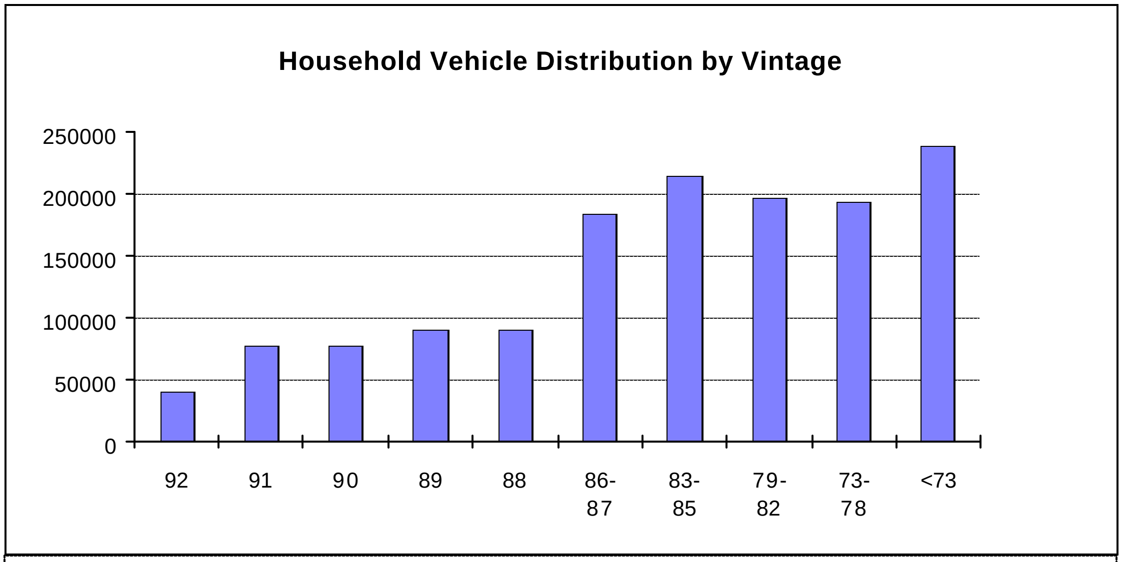
[10] Commercial fleets' VMT figure is from the fleet survey conducted by University of California at Irvine and Davis in 1994.

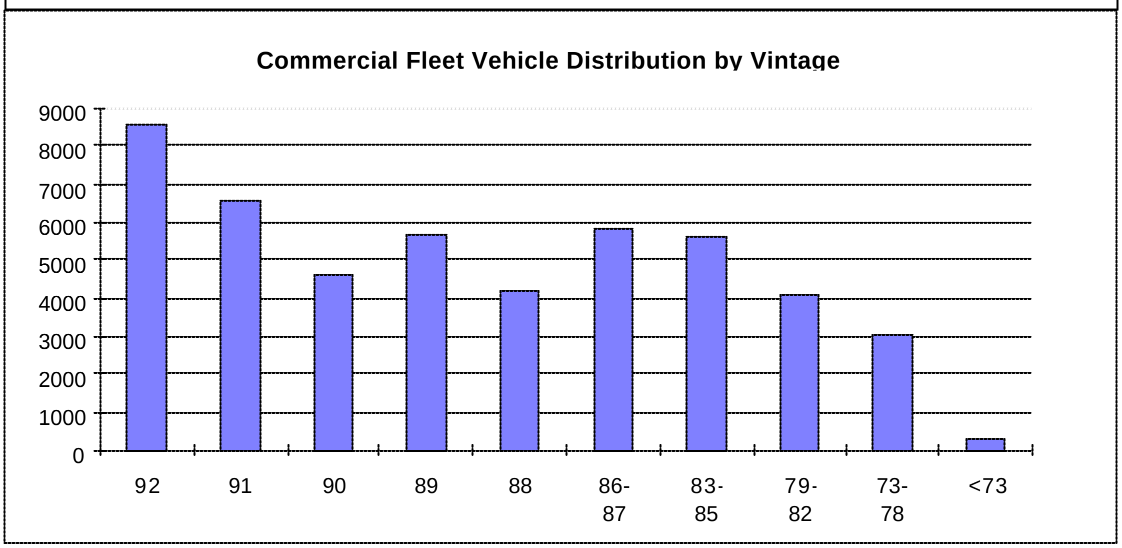
since commercial entities are substantially fewer and each possess a higher number of vehicles. Most AFV studies, however, have concentrated on the household demand. (Karfisi, Upton, and Agnew, 1978; Beggs, Cardell, and Hausman, 1980; Train, 1980; Hensher, 1982; Calfee, 1985; Bunch et al, 1992; Brownstone & Ren, 1994; Ren, et al, 1995.) In this study, I focus on the commercial fleets. I use a data set that surveys light-duty commercial and local government fleets, excluding State and Federal government fleets, emergency fleets, and rental fleets.

Figure 1

Vehicle Model Year Distribution For Commercial Fleets and Households

Source: 1993 vehicle registration data from California Department of Motor Vehicles (DMV)[11]





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[11] First, a random sample from the California Department of Motor Vehicle's records of all registered vehicles is obtained. This sample consists of 1.8 million records. Then, an algorithm is implemented which looks for words that could identify a record as a business establishment, a household, a state government office, a local government office, or other establishment types. Thus, records are categorized into several distinct categories. The Commercial Fleet's count includes businesses that have over 10 vehicles. The household vehicles comprise over 70% of all records in the 1.8 million sample.

2.3 PURPOSE OF THIS DISSERTATION

2.3.1 Government Intervention Issue

Is it necessary to have government mandates to encourage AFV use? To address this question, I estimate the degree of market penetration of AFVs with and without government intervention. Even though some vehicle types are available with alternative fuel technology, these AFVs are still more expensive and perform less favorably than their gasoline counterparts. Higher capital cost, limited range, higher refueling time, lower refueling station availability, and limited cargo space make AFVs unattractive to most vehicle purchasers. The air pollution reduction feature of AFVs, which is their favorable characteristic, does not enter in the cost consideration of most consumers. We can expect that for most purchasers, the private cost of operating their vehicles does not include the social cost of air pollution. Vehicle purchasers do not have an incentive to absorb higher capital costs and lower performance of obtaining AFVs simply because they are less polluting. Since typical vehicle users are currently not paying for their vehicles' tailpipe emission, there is no incentive for them to switch to AFVs . Thus, we can expect that AFVs diffusion in the market solely through market forces would be slow, if ever, unless vehicle users were to be penalized for their vehicles' emissions. In this dissertation, I will provide some empirical evidence that supports this argument. I also study different policy scenarios and their impact on the AFV diffusion.

2.3.2 AFVs Technology Development

How could AFVs improve technologically to become more competitive in the market? What values do vehicle purchasers place on each vehicle attribute and how do they perceive tradeoffs between these attributes? For example, what is the value of increasing an electric vehicle's range by ten miles, or decreasing a compressed natural gas vehicle's refueling time by ten minutes? I will provide some empirical answers to these questions.

2.3.3 Targeting the Right Consumer Groups

We also need to know what vehicle purchaser groups are more likely to be the first to adopt AFVs and why. This information is crucial for marketing purposes in launching a successful campaign for AFVs so that the more likely adopters could be targeted directly. Also, policy-makers need this information to design proper incentive programs (subsidies and /or fines) that would motivate non-adopters to consider AFVs. I address these problems in this research.

2.3.4 Diffusion Rate Under Different Assumptions

Assuming various technologies and incentive programs, I answer the following questions. Are the current types of AFVs marketable? What would be the diffusion rate of current AFVs? How would technological improvements in AFV attributes such as range and refueling time affect their demand? How would government intervention affect AFV diffusion? I simulate some policy and technology states and calculate the diffusion rate for each state.

2.4 LITERATURE REVIEW

2.4.1 Technology Diffusion Literature

Diffusion of a new technology takes place in two phases. In the initial phase, the technology is unknown and only a few innovators adopt the technology. Then, a large number of imitators follow the innovators and adopt the new technology. The initial phase is usually slow but very crucial in the success of the product diffusion. Profitability and competition are reasons that affect adopters' decision to adopt or not. (For a complete analysis see Reinganum, 1989)

In the initial phase, as new firms adopt the new technology, they could cause positive or negative externalities for the later adopters. Negative externalities occur when new entrants reduce the profitability that the previous entrants have enjoyed. Positive externalities occur when networking externalities exist. Dybvig and Spatt (1983) provide an analysis of adoption when adoption externalities are public goods. They introduce a model of the firm profit function when *networking* (positive) externalities exist in new technology diffusion. They consider government intervention and present an optimal intervention model. This model could be applied to situations like computer technology, standards such as the metric system, and computer languages. The infrastructure networking externalities in the case of

AFV adoption could also fit in the model. For AFVs, these externalities include the following: (1) service station availability and refueling training, (2) mechanical expertise and familiarity, and (3) safety and performance testing.

Farrell and Saloner (1986) explore the networking effect. They consider the relation between the installed base of an old technology and the adoption of new technology. They argue that when a new product is compatible with the old installed base, the new product gets adopted much faster. They investigate the conditions under which the adoption may be delayed because of "excess inertia", or when the extent of the installed base of the old technology delays the switch to the new, superior technology even when the new technology would be more efficient. AFVs are more efficient with respect to air pollution (and noise pollution in the EV case) but less efficient in most other vehicle attributes than gasoline vehicles. AFVs have generally higher costs, lower range, higher refueling time, and lower cargo capacity than gasoline vehicles. Thus, their diffusion is expected to be slow, if it occurs at all. But the "installed base" of gasoline service stations, repair and maintenance facilities, and consumers' driving and refueling practices may delay the AFV adoption even more. How does this "installed base" affect potential adopters of AFVs? I will provide some empirical answers to this question by exploring the impact of on-site refueling, service station availability, and on-site maintenance facility on AFV diffusion.

Some of the technology diffusion literature has focused on the relation between market structure and new technology adoption. Hannan and McDowell (1984) present an empirical study of the banking industry and ATM technology adoption. They find that larger firms had a higher conditional probability of adoption of this new technology. I will also explore the relation between firm size and AFV adoption later in this dissertation.

Another way to assess the value of technology developments to the consumers is by estimating hedonic models. Here, the valuation of new technology attributes are measured using revealed preference data. A good example is Trajtemberg (1989) who estimates the welfare enhancing value of technological developments in the case of Computed Tomography Scanners (CAT scanners). I do not use hedonic models here, since I use a stated choice hypothetical data as the basis of my valuation method. The use of hedonic models of vehicle attribute values could be an option for future studies when the actual choices of alternative fuel vehicle adoption are observed, assuming that any AFV incentive programs could be satisfactorily controlled in the studies.

2.4.2 Transportation Literature

Past research on the subject of the demand for AFV by the commercial fleets is limited. I examine this literature from four angles: (1) the type of alternative fuel vehicle, (2) the universe of the fleet vehicles, (3) the kinds of fleet characteristics thought to be important in AFV choice, and (4) modeling practices.

2.4.2.1 Alternative Fuel Vehicles Type

Many studies explore the fleet market potential for one type of alternative fuel only. Shonka (1980) and Berg, et al (1984) study the potential market for electric vehicles. Easton Consultants (1991), Beiderman and Blazek (1990), and Marshment (1991) explore the fleet market for natural gas vehicles. Methanol vehicles' demand by the fleet market is investigated by Wachs and Levine (1985) and Lareau (1990).

With the increasing regulatory pressure to substitute a portion of fleet vehicles with alternative fuel vehicles, there is a more urgent need for a comprehensive fleet vehicle demand model that would explore the demand for different AFVs in the presence of more than one type of alternative fuel. In this study, the demand for three major types of the AFVs are investigated simultaneously. This is a more realistic setting than the dedicated studies are. Actual fleet managers will be confronted with choosing among several types of alternative fuel vehicles, once AFVs become widely available. The fuel type variety as well as the large scale survey instrument that will be discussed later have created the foundation for the most comprehensive AFV fleet demand study to date.

2.4.2.2 The Universe Of The Fleet Vehicles

The population of the fleet vehicles is not satisfactorily determined in the past research because of (1) inconsistencies in the definition of fleets, (2) oversampling of the larger fleets, and (3) non-representative sampling practices (For a comprehensive analysis see Miaou, 1992). A Dunn and Bradstreet list of firms, for example, has been a favored source of fleet population (See Berg, et al, 1984; Hill, 1987). The Dunn and Bradstreet list contains only larger organizations, most probably with larger vehicle fleets, and is not even a complete list of larger fleets.

In this study, I overcome these problems by using a representative sample of the California fleets compiled by the Institute of Transportation Studies at the University of California, Irvine and Davis. Here the fleet is defined as a commercial or local government establishment with ten or more light duty (up to 14,000 pounds) vehicles at site. From the comprehensive list of all vehicles registered in California by the Department of Motor Vehicles, a list of the sites with ten or more registered vehicles was obtained. Rule-based algorithms were employed to eliminate residential, state and federal government, rental, and emergency vehicle fleets. This is because CARB's regulation applies only to certain commercial fleets. Slight differences in registration names and addresses were also identified and integrated. Following this procedure, the most comprehensive list of the fleet population in California was created. The survey that I use in this study was conducted on a sample from this list.

2.4.2.3 Important Characteristics Of New Fleet Purchases

NAFA (1991) and Runzheimer (1991) report that the majority of business fleets consider "initial purchase price" and "job suitability" as the most important factors when purchasing or leasing new vehicles. Runzheimer's survey suggests that 19% of the leading fleet management consider the *cost of maintenance and repair* as the most important criterion for choosing their vehicle fleets; 16% say that *vehicle disposal price* is the most important criteria; 13% cite *new car price* as the most critical point; and 12% regard the *cost of gasoline* as the most important criterion for selecting vehicles for their business fleet. Compare this criteria list with that of the government fleets: 37% of government fleet managers cite *cost of maintenance and repair*, 28% cite *the cost of gasoline*, 11% regard *the quality of car maintenance and repair*, and 8% consider *the new car price* as the most important criterion to select their fleet vehicles. Runzheimer's study concludes that government fleet managers may be less concerned with the initial purchase price.

Nesbitt (1993) reviews the previous research on the fleet demand for AFV as well as reports on the findings from his 29 one-on-one interviews and seven focus groups. The interviews were conducted in Sacramento and Los Angeles. He finds that other than cost, the main barriers in using EVs and NGVs (natural gas vehicles) in fleets are practical limitations. Operational restrictions, such as range limits and recharging times, are the biggest concerns for EVs. Fuel availability and safety are the primary NGV concern. The resale value is important to some fleet managers; however, it is not a major purchase criterion. Nesbitt also finds that large fleets are more informed and more willing to try EVs and NGVs. Smaller fleet organizations, on the other hand, indicate that they would wait for larger fleet organizations to assume the initial risks associated with purchasing AFVs.

Shonka's study (1980) is based on a survey of fleet managers. His study finds that the respondents were willing to pay on average an extra $1.03 for each additional mile of range (with the base range being 100 miles).

These kinds of preliminary findings regarding the operational behavior of fleets and the perceived tradeoffs need to be tested in a uniform manner. Our detailed survey provides a wealth of resources to investigate the validity of some of the previous hypotheses in a micro manner.

2.4.2.4 Modeling

Most fleet studies so far have been descriptive analyses of fleet composition with some conjectures about future trends. Determination of the likely market penetration has usually stopped at the market potential of the types of vehicles that could be replaced by existing AFVs. Berg, et al (1984) and Berg (1985) are among the most cited of these studies. Berg (1985) is an analysis of the EV fleet market potential based on a survey conducted during fall of 1982. A sample of fleet operations is drawn from the Dunn and Bradstreet list of fleets in the United States. The survey consists of 583 telephone interviews. The goal of the study was to examine the "potential" market rather than the "penetration" of the electric vehicles in the fleet market. "Potential" market referred to the upper limit of the possible number of fleet vehicles that could be replaced by the EVs. Berg avoids the issue of "penetration" on the ground that it is based on highly qualitative assumptions and procedures. He estimates that the "potential" market for the electric vehicles across both commercial and household sectors is between 2.5 and 7 million out of 12.7 million light duty vehicles.

A few studies have developed some formal models of the AFV fleet demand. Hill (1987) constructs a theoretical derived demand model of fleet demand for electric vehicles. He specifies an econometric model employing a heteroscedasticity-corrected double Tobit model for his analysis. He uses an experimental design instrument to generate data for a nine-cell matrix of life-cycle cost and range combinations. Each respondent is given one randomly chosen combination of life-cycle and range from the nine cell matrix and asked to indicate if a vehicle of the sort described would be useful in his vehicle fleet operation, and if so how many he or she would use. The question was included at the end of the National Commercial Vehicle Fleet Managers survey. A total of 474 fleet managers responded to the questions. One problem with this study is that the sampling practice resulted in a sample bias towards larger fleets. Another shortcoming is lack of sufficient control for firm specific variables such as industry type and vehicle usage. Other problems with this work include the constraint of looking at only one fuel type and attempting to measure the tradeoffs between only two vehicle attributes with limited variations. For instance, refueling time, which is an important limitation of AFVs, is not considered.

A richer set of econometric modeling procedures has been developed with respect to the household demand for the AFVs. Train (1980) is one of the most cited household vehicle choice studies. Ren, et al (1995) takes this approach further by employing a more elaborate survey instrument. Ren, et al. develops a conditional logit model with the current vehicle holdings and household characteristics as well as fuel specific attributes predicting the probabilities of each fuel type choice (choices are EV, NGV, methanol, and gasoline) based on some stated choice hypothetical scenarios.

For the fleet AFV demand, I extend the household choice models to the commercial sector, incorporating some of the important covariates found in the previous fleet studies such as cost, range, and vehicle body type. I include some additional covariates that are specific to the commercial sector fleet study. These include industry type, vehicle duty function, and in-house maintenance and service facilities. I also examine issues discussed in the technology diffusion literature. I consider the impact of infrastructure, firm size, and networking effects on fuel choice by using proxy variables for these covariates in the choice model.

CHAPTER 3

THE DATA

3.1 The Survey

The data consists of a commercial fleet survey conducted by University of California's Institute of Transportation Studies at Irvine and Davis in the Spring of 1994. The sample of fleet sites was selected from the motor vehicle registration records. An algorithm was implemented that screens the commercial and local government fleets. The sample was site based and in some cases multiple locations of a firm were interviewed. Sample sites were drawn with probability proportional to their fleet size.

The survey was conducted in two stages. First, a CATI (Computer Assisted Telephone Interview) was designed to identify eligible firms. Eligible firms were those with at least ten vehicles in their organization that weigh less than 14,000 pounds each. If a headquarter was reached where vehicles were registered but not operated, the interviewer tried to locate and contact the largest fleet site where vehicles were operated. Once an eligible site was reached, the interviewer asked to talk with the fleet manager. Detailed information was obtained about the organization's specific characteristics and its vehicle fleets. A total of 2715 interviews were completed in this stage of the survey.

Second, following the CATI, a customized mail-out questionnaire was sent to the respondents. Two customized hypothetical vehicle choice sets for two of the firms' vehicle body types were included in the mail-out. Of the 2715 CATI respondents who completed the CATI part of the survey, 2131 also returned the mail-out questionnaires.

3.2 Stated Preference Modeling

The objective of this study is to find fleet managers' preferences for vehicle fuel types. This is best accomplished by observing consumers' actual choices among vehicles running on different fuel types, that is, by their revealed preferences. Unfortunately, since some of these fuel types are not commercially available at the present time, it is impossible to observe consumers' actual choices. An alternate method of studying preferences is stated preference modeling. Using stated preferences, as opposed to revealed preferences, to model consumers behavior, one can study the expected reception of new and future technology.

There are two broad types of stated preference experiments: (1) A set of combinations of attributes which define a product or a service is presented to the respondent. The respondent is asked to either rank or rate his preferred choices among a set of possible choices. (2) An individual is asked to choose one of the combinations of attributes. Here, no information is sought on the choices that are not picked. (Hensher, 1994) The advantage of the first approach is that information on all the choices are gathered. The disadvantage is that the data by itself does not allow for directly predicting the market share and thus some transformation of the data to accommodate market share "predictions" are necessary. This problem does not apply to the second approach.

However, using the second approach, the information on the second choices and so on is not available. For the stated preference experiment, we designed a set of SP scenarios that combines the best features of both these approached. In each SP experiment, we gave the respondent three scenarios that describe three vehicles as to its fuel type, price, operating characteristics, and other attributes. Each respondent is asked to divide up his or her entire vehicle fleet between the three given choices. This way, we capture the features of both types of SP methods by giving the respondents both a range of attribute levels and a way of ranking the choices. We generate a total of 64 different experiments which allow us to alter attribute levels for estimating the importance of each attribute in the respondents choices. At the same time, we do not lose information on the second and third choices because the respondents indicate how they would divide up their vehicle fleets between the three choices. These responses can readily be interpreted as percentages of the fleet chosen for each fuel type and thus they can be used as choice weights in a discrete choice model. The probabilities assigned to each alternative, then, can be estimated from the responses to these hypothetical scenarios.[12]

A major potential problem with stated preference modeling is that the respondents may misrepresent their true preferences or actual choices for several reasons: (1) The respondents may be careless in responding to a questionnaire. We tried to detect this potential problem by asking about the same information in different parts of the survey and

[12] For an overview of experimental design and its use in the Stated Preference survey, please see Louviere, 1993. For an overview of the Stated Preference method, please see Hensher, 1994.

comparing the inconsistencies. The responses with severe inconsistencies then were eliminated from the estimation. (2) The respondents may not understand the question correctly or may not be familiar with technical attributes when describing vehicles. Eisner (1987) discusses this issue. We believed that this potential problem was minimal in our sample because our respondents were professionals whose specialty were managing vehicles and thus could understand the technical description of the vehicles. (3) The respondent may intend to present a false image. This could be a potential problem especially since we were dealing with sensitive environmental issues and one may worry that some firms may want to falsely project the image of being AFV friendly. This type of firm may actually say that they would purchase electric vehicles but only purchase one or two token vehicles in reality. We cannot eliminate this concern completely. However, we tried to alleviate it by having an open-ended response section for SP vehicle choice, and by dividing the stated number of vehicles in each fuel type category into a number that would indicate the percentage that it represents out of all vehicles in the firm's fleet.

There are other potential problems with the SP data. Koskenoja (1996) reviews this literature in the context of travel time reliability. One potential bias is *framing of choices*. Framing of choices refers to the bias caused by the way choices are worded. That is, if we presented the same information in a different form, it may have an effect in the outcome. We tried to minimize this problem by listing all attributes of the three choices in each experiment side by side in three columns. We also took extra care in wording of each question and tried to minimize questions or descriptions which may have some alternative interpretations.

Each choice set in the Stated Preference (SP) survey included three of the following four fuel types: electric, compressed natural gas (CNG), methanol, and gasoline. The fuel type that was not included in the first SP scenario was always included in the second SP scenario. In this way each respondent was given all four fuel types as choices, except for a small subgroup of firms which only had one type of vehicle in their fleets and therefore did not get a second set of SP scenarios. Attribute levels variations resulted in having 64 attribute-level / fuel-type cells. Respondents were randomly assigned one of these 64 cells. A detailed description of the attributes for each of the hypothetical choices was included. The attribute list included fuel type, range, capital cost, operating cost, and tailpipe emission level. A complete list of the attributes is featured in Table 1. A sample mail-out for the two stated preference scenarios is shown in Appendix I.

Table 1

Variable Descriptions And Variations

Name	unit	Description
Capital Cost	$10,000	Cars & Station Wagons, Minivans, Full Size Vans, Compact Pickups, Full Size Pickups Electric: 1.4 ; 1.7 ; 2.0 CNG: 1.4 ; 1.6 ; 1.8 Methanol: 1.3 ; 1.5 ; 1.7 Gasoline: 1.3 ; 1.5 ; 1.7 Small & Medium Shuttle Buses Electric: 8.0 ; 10.0 ; 12.0 CNG: 4.0 ; 5.0 ; 6.0 Methanol: 4.0 ; 5.0 ; 6.0 Gasoline: 4.0 ; 5.0 ; 6.0 Trucks (6,000-14,000 Ibs) 5.0 ; 6.0 ; 7.0
Range	100 miles	Electric: 0.60, 1.00, 1.50 CNG: 0.80, 1.50, 2.75 Methanol: 1.50, 2.00, 2.50 Gasoline: 2.50, 3.00, 3.50
Operating Cost	cents/ mile	Electric vehicle cost for day charge 8, 12, 20
	cents/ mile	Electric vehicle cost for overnight charge 2, 4, 6
	cents/ mile	CNG, Methanol, & Gasoline refueling cost CNG: 7, 9, 11 Methanol: 9, 11, 13 Gasoline: 8, 10, 12
On-Site Refueling Unit Cost	$	CNG slow-fill unit cost: 2,000; 3,000; 4,000
	$	CNG fast-fill unit cost: 75,000; 100,000; 120,000
	$	Methanol on-site pump cost: 45,000; 50,000; 60,000
On-Site Refueling Currently In Place	dummy	Gasoline = 0 if no on-site refueling = 1 if currently has on-site refueling pump

Name	unit	Description
		(from survey responses)

Table 1 (continued)

Variable Descriptions And Variations

Name	unit	Description
On-Site Refueling Time	hours	Electric vehicle on-site recharging time: 3, 4, 6
	hours	CNG on-site slow-fill refueling time: 1, 2, 4
	minutes	CNG on-site fast-fill refueling time: 10, 15, 30
Service Station Availability Relative To Gasoline Stations	ratio to every 10 gasoline station	Electric: 1, 2, 5 CNG: 1, 3, 7 Methanol: 1, 3, 7 Gasoline: 10
Refueling Time At Service Station	minutes	Electric: 20, 30, 60
	minutes	CNG: 5, 10, 15
	minutes	Methanol: 7 Gasoline: 7
Dual Fuel Capability	dummy	Electric vehicle only = 0 Electric vehicle with gasoline extender (Hybrid) = 1
	dummy	CNG only = 0 CNG with gasoline capability = 1
Home Refueling Availability		CNG: 0 = not available $2,000 = cost of home unit $4,000 = cost of home unit
		Electric home recharging always available for body type = cars and station wagons
Cargo Capacity	relative to gasoline vehicles	Electric: 0.6; 0.7; 0.8
	relative to gasoline vehicles	CNG: 0.7; 0.8; 0.85
		Methanol: same as gasoline
Total Vehicles Of Similar Type On Road In California		10,000; 50,000; 100,000
Tailpipe Emissions	relative to new 1993 gasoline	Electric: zero CNG: 10%, 25%, 40% Methanol: 25%, 40%, 60%

Name	unit	Description
	vehicle	Gasoline: 25%; 60%; 100%

3.3 Description Of Sampled Fleets

The total number of vehicles in our sample is 136,000. Approximately 50% of the vehicles are in fleet sites of 200 or more vehicles. Roughly 50% of the sample fleet sites have less than 25 vehicles.

3.3.1 Industry Segmentation and Fleet Characteristics

I have divided the sample into twelve industry types. The industry types are classified using a three-pronged approach: (1) the fleet managers' selection of pre-described industry categories which are taken from two-digit Standard Industrial Codes (SIC), (2) my own assignment of industry types based on an open ended question asking the fleet managers to describe the kind of work that is done at the establishment, and (3) comparison of the results from steps (1) and (2) with the establishments' names[13]. The industry types are coded into twelve customized categories. This coding procedure permits a more up-to-date classification of the industries. For example, a new category of "household services" is created consisting of local home-related small businesses such as gardening, plumbing, heating and air-conditioning repair, and so on. The list of these industry categories, their respective fleet numbers, and their average fleet size in the sampled fleets are shown in Table 2.

[13] I thank Jane Torous for her assistance in assigning new classifications for industry types.

Table 2

Descriptive Statistics by Fleet Industry Types

Fleet Types	*Number of Fleet Sites*	*% of Total Fleet Sites*	*Average Fleet Size*	*Average Annual VMT*
Agriculture	94	4.6	28	22,300
Automotive Business or Service	66	3.3	22	28,300
Banking & Insurance	56	2.8	44	18,400
City & County Government	291	14.4	174	16,500
Construction & Contracting	263	13.0	30	24,500
Household Services and Trades	256	12.7	30	22,300
Manufacturing	230	11.4	49	23,700
Miscellaneous Industries	32	1.6	113	16,700
Retail & Wholesale Sales	133	6.6	37	27,900
Services for Business & Professional Organizations.	202	10.0	32	28,000
Schools (public & private)	195	9.6	65	14,000
Transportation & Communications	162	8.0	109	36,000
Unknown	43	2.1	38	

The top five industry categories of fleets in our sample are city and county government (14.4%), construction and contracting (13.0%), household services and trades such as plumbing and heating (12.7%), manufacturing (11.4%), and services for business (10.0%). Our sample excludes vehicle rental company fleets and federal and state government fleets.

The variation of average annual vehicle miles traveled (VMT) across different types of firms is also interesting to examine. City and county agencies have the highest vehicle fleet size, while they have lower average annual VMT compared to all but one other industry group.

3.3.2 Firm Characteristics

One important characteristic of fleet sites is whether or not the site is equipped with maintenance, service, and refueling facilities. Some clean fuel mandates initially only target fleet sites with on-site refueling capabilities. We have included questions about maintenance and refueling practices in the survey. Table 3 lists statistics on on-site refueling capability of the firms by industry types. Most "city and county agencies" (76%), "schools" (72%), and "agriculture" organizations (71%) in our sample have on-site refueling facilities. "Banking / insurance industry" and "household services", on the other hand, are least likely to own on-site refueling facilities.

Table 3

On-Site Refueling Capability by Industry Type

Fleet Sector	***On-site refueling capability (%)***			
	has presently	***not now/ feasible***	***not feasible***	***unknown***
Agriculture	71	25	4	0
Automotive Business or Service	24	49	27	0
Banking & Insurance	14	11	66	9
City & County Government	76	20	4	0
Construction & Contracting	41	39	17	3
Household Services and Trades	20	40	34	6
Manufacturing	41	33	23	3
Miscellaneous Industries	28	38	28	6
Retail & Wholesale Sales	35	38	24	3
Services for Business & Professional Organizations.	25	32	40	4
Schools (public & private)	72	21	5	2
Transportation & Communications	42	27	29	3
Total sample	43.8	30.8	22.4	2.9

3.3.3 Vehicle Characteristics

Table 4 shows the list of vehicle frequencies by vehicle body types. The vehicle body types are categorized into seven distinct groups in our survey questions. We ask the respondents to list the number of fleet vehicles in each of these seven categories. The category of *Cars and Station Wagons* refer to all types of cars in the following categories: minicars, subcompact cars, compact cars, intermediate cars, large cars, and sports cars. We do not provide specific categories for *small sport utility* and *mini sport utility. Full-size pick-ups* are the fleets' most popular vehicle types followed by *cars and station wagons*.

Table 4

Fleet Sites' Frequency by Vehicle Body Type

Vehicle Body Type	***Total # of Fleet Sites***
Cars	823
Minivans	310
Full-size Vans	523
Compact Pickups	560
Full-size Pickups	1019
Small Buses	69
Trucks <14,000 lb. GVW	587

CHAPTER 4

METHODOLOGY

4.1 Theoretical Framework

One way to understand how a firm acquires its vehicle fleet is to model the fleet manager's choice process. The fleet manager knows the general guidelines of the company regarding the vehicle fleet transactions. He or she makes his/her choice by judging which vehicle best meets the firm's guidelines. The guidelines differ among firms with different characteristics. Therefore, the choice model should include the firm's characteristics as explanatory variables. I assume that the fleet manager derives the highest utility when he or she picks the best alternative from a choice set given the firm's guidelines. I assume that the fleet managers have the sole authority to make all the vehicle fleet decisions including replacement, disposal, and purchase of vehicles.

In the stated preference scenarios, each fleet manager faces two sets of choices for two body types from the firm's vehicle fleet. The respondent is instructed to replace the entire fleet of the particular body type. He or she can choose any combination of the vehicle fuel choices that yields the number of vehicles the firm currently has in that category. The levels of vehicle attributes are assigned randomly to the respondents.

The fleet manager chooses the alternative that yields the greatest benefits (utility). Formally, the indirect utility function for fleet manager *n* choosing alternative *i* is given by the following equation (McFadden, 1974):

$$U_{in} = V_{in} + e_{in}$$

where (n = 1,..., 2131; number of observations), (i = 1,2,3,4; for electric, CNG, methanol, and gasoline respectively), V_{in} is the deterministic component of the utility function, and e_{in} is the random component of the utility function. I assume e_{in} is independently distributed with extreme value distribution. I further assume V_{in} to be a linear combination of known characteristics of the firms and the SP vehicle. Thus,

$$V_{in} = b' X_{in}$$

where X_{in} is the vector of explanatory variables including all observed characteristics specific to the firm, its vehicles, and the SP choice attributes, and b is the coefficient vector for X_{in} .

The next task is to estimate the probability that firm n chooses alternative i given the set of the three (fuel) choices that were presented to the respondent in the stated preference scenarios. I follow McFadden (1974) and define P_{in} as the conditional probability that firm n chooses alternative i:

$$P_{in} = P(y_{in} = 1) = \frac{\exp(V_{in})}{\sum_{j=1}^{4} \exp(V_{jn})} = \frac{\exp(b' X_{in})}{\sum_{j=1}^{4} \exp(b' X_{jn})}$$

where y_{in} is the vector of dependent variables: $y_{in} = 1$ when alternative i is chosen by the fleet manager n, and $y_{in} = 0$ otherwise.

The probability of choosing each fuel alternative is estimated by using the fleet manager's responses to the stated preference survey in the above model. Each firm is taken as one unit of observation. Each fleet manager is allowed to allocate the firm's total number of vehicle fleet of the SP body type into one, two, or three categories in the SP scenarios.

The indicated number of vehicles for each fuel type is converted to a percentage of the total number of vehicles for that particular vehicle body type in the respondent's vehicle fleet. These percentages are then entered into the model as *fraction weights*, each between zero and one. For example, a weight of zero is assigned to the choices that were not picked at all by the respondents. The log likelihood function is now as follows:

$$L = \sum_{n=1}^{N} \sum_{i=1}^{4} w_{in} y_{in} (b' X_{in} - \ln \sum_{j=1}^{4} \exp(b' X_{jn}))$$

where w_{in} is equal to the *fraction weight* of firm n choosing fuel i as described in the previous paragraph.

4.2 Model A

I estimate the conditional multinomial logit model constructed from the stated preference responses where vehicle choice is the dependent variable and firm's industry, vehicle body type, vehicle function, and fleet site size interacted with the fuel constants and SP attributes are the explanatory variables. Gasoline fuel choice is taken as the base for the fuel choice estimation. The results from the model are listed in Table 5.

Some estimated coefficients stand out from the rest. When vehicles are used for "service/maintenance calls", the interaction coefficient is positive and significant. This indicates that firms using their vehicles for this function show a weaker dislike for the electric vehicles over the gasoline vehicles than the surveyed firms did in general. The same story can be told for vehicle body type "compact pick-up"._Schools show the lowest dislike for electric vehicles when all else is equal. The agriculture industry, however, strongly prefers gasoline vehicle to the electric vehicles. Agricultural operations outside the more polluted urban areas are less likely to be regulated with respect to their vehicle fuel type. With less regulatory pressure for the conversion to alternative fuel vehicles, the strong negative preference for electric vehicles is understandable. Perhaps, less exposure to the electric vehicle information and on-road experience could explain the observed aversion of the agriculture industry to electric vehicles.

Organizations with at least 120 vehicles at the surveyed site showed a more favorable preference for CNG vehicles. Larger fleets are historically more likely to be regulated with respect to their fleet types. Alternatives to regulation XV in California are being proposed which allow replacement of lower emitting vehicles for the carpooling schemes initially proposed. Larger fleets' managers and staff have had more exposure to CNG vehicles compared with the electric vehicles. Larger fleets are also more likely to have on-site refueling facilities which would make it easier to work with fuels that are less common.

Both "city and county agencies" and "schools" show a stronger preference for CNG vehicles over gasoline vehicles when all else is equal. The regulatory influence could be the reason why the interaction of the CNG constant with "retail and wholesale firms" as well as CNG constant interaction with "banking / insurance / real estate firms" have negative signs, which means a lesser chance that either of them pick CNG compared to the rest of the firms. Both these industries are thought to be least regulated industries with respect to their vehicle fleets' emissions.

CNG vehicles described in the SP scenarios may be dedicated to CNG only or capable of running on gasoline as well. When CNG vehicle has dual fuel capability, it is chosen more often than when it is a dedicated CNG vehicle, all else being equal.

"Schools" and "transportation & communication" industries show the least preferences for methanol vehicles. Commonly, it is believed that methanol vehicles could explode more frequently than others. This belief may be responsible for the more negative perception of fleet managers in "schools" and "transportation & communication" organizations, since both these industries' fleets are used mainly for transporting people. "Agriculture" industry, on the other hand, seems to have a more favorable view of the methanol vehicles compared to the other firms in the sample. In fact, agriculture firms show indifference between methanol and gasoline vehicles. I earlier discussed that agriculture firms showed the least preference of any group for the electric vehicles. Methanol appears to be the alternative fuel of choice by agriculture industry. Perhaps, ease of conversion between the gasoline and methanol fuels is one reason for this preference. Also, there is less strict air quality standard affecting agriculture industry's fleets, since they are mostly located in sparsely populated areas. Therefore, using methanol, which is only slightly less polluting than gasoline, may suffice to meet the air quality standards. Another explanation could be a possible confusion between methanol and ethanol by the agriculture industry fleet managers. Ethanol is a more favored alternative fuel because of its production dependence to the agriculture industry.

Model A's results also indicate that improvements in recharging times of electric and CNG vehicles would have a positive effect in their marketing success. Some alternative fuel vehicles such as electric and CNG vehicles lave reduced cargo capacity due to their bulky batteries or fuel tanks. The cargo capacity for EV and CNG vehicles in the SP scenarios vary between 60 percent to 85 percent of the conventional gasoline vehicles. Our surveyed fleet managers indicate a positive preference for larger cargo capacity. Thus, improvements in the battery size for electric vehicles and in the fuel tank design for CNG vehicles should expand their appeal in the market place.

Another potentially important factor in the adoption of AFVs could be the infrastructure availability for alternative fuels. How many service stations should offer refueling facilities for AFVs before the consumer feels at ease to switch to the non-conventional fuels? When the vehicle attributes in the SP scenarios were described, the respondents were given a ratio of refueling station availability with respect to the gasoline stations. These ratios range from "1 out of 10" to "7 out of 10" stations. The estimated coefficients in Model A shows a positive preference for more AFV refueling stations relative to gasoline stations. This result indicates the importance of the infrastructure investment in the success of any AFV implementation program.

Model A also includes estimating a coefficient for "tailpipe emissions". The covariate of "tailpipe emission" for electric vehicles has a value of zero, for CNG vehicles could be at 10 percent, 25 percent, or 40 percent level of the new 1993 gasoline vehicles of the same body type, and for methanol vehicles could be 25 percent, 40 percent, or 60 percent "tailpipe emissions" of 1993 gasoline vehicles. The estimation results show an overall lack of sensitivity to higher "tailpipe emissions", except for "city and county" agencies and "schools". For these two groups, lower emission levels are extremely important. This is evident by a significant negative coefficient estimate of 0.4 for these two groups combined. The lack of sensitivity of private firms to emission levels is expected since the private cost of emission is practically zero for drivers. There is no incentive for the drivers to opt for cleaner fuel vehicles unless the public cost of emission is somehow transferred to the individual drivers. Programs such as *remote sensing* for charging emission prices may be the solution.

Table 5

Model A: A Conditional Logit Model of Fuel Choice

Base choice = gasoline vehicle	Coef.	t
EV constant (all observations)	-0.686	-1.78
EV constant * [SP vehicle body type = compact pick up]	0.307	2.28
EV constant * [SP vehicle function = service/maintenance calls]	0.342	3.18
EV constant * [organization type = schools]	0.776	4.19
EV constant * [organization type = agriculture related firms]	-0.655	-1.88
EV day-time recharging cost, cents/mile.	-0.015	-1.53
EV on-site refueling time in hours.	-0.066	-1.58
EV service station recharging time in minutes	-0.004	-1.48
EV * Capital cost of vehicle for all firms but those in construction industry.	-0.056	-1.62
EV * capital cost * [organization type = construction firms]	-0.087	-1.53
EV * range	-0.001	-0.53
EV * range * [SP vehicle function = transport / shuttle people]	0.003	1.93
EV * [# of refueling stations relative to gasoline stations]	-0.709	-2.10
EV cargo capacity compared to gasoline vehicles	0.038	0.17
CNG constant (all observations)	-0.469	-2.74
CNG constant * [organizations with fleet site size of at least 120 vehicles]	0.420	3.01
CNG constant * [organization type = city and county agencies]	0.310	2.43
CNG constant * [organization type = schools]	0.443	2.73
CNG constant * [organization type = retail and wholesale firms]	-0.254	-1.46
CNG constant * [organization type = banking, insurance and real estate]	-0.735	-1.90
CNG dual fuel capability: 0 = CNG only; 1 = can also run on gasoline.	0.293	3.57
CNG service station refueling time in minutes	-0.026	-2.53
CNG cargo capacity compared to gasoline vehicles	0.182	1.40
Methanol constant (all observations)	-0.194	-2.05
Methanol constant * [organization type = schools]	-0.297	-1.71
Methanol constant * [organization type = transportation/ communication]	-0.275	-1.69
Methanol constant * [organization type = agriculture related firms]	0.343	1.85
Gasoline on-site refueling available	0.272	3.54
Capital cost of vehicle for all but those firms in construction industry.	-0.231	-4.83
Capital cost * [organization type = construction firms]	-0.128	-1.17
Vehicle range in miles interacted with all observations <u>excluding</u> those with SP vehicle function = transport/shuttle people.	0.002	6.04
Vehicle range * [SP vehicle function = transport / shuttle people]	0.001	2.33
# of refueling stations relative to gasoline stations	0.316	2.99
Operating cost in cents/mile (CNG, methanol, gasoline)	-0.059	-5.07

Base choice = gasoline vehicle	Coef.	t
Tailpipe emission * [organization type = a city/county agency or a school]	-0.396	-2.60

4.3 Model Specification Tests

For model A, I use a test proposed by Hausman and McFadden (1984) to detect violations of the IIA assumption. This test is generally referred to as the *Hausman Test*. A nested model, shown in Figure 2 as model B, is tested against the multinomial choice model (model A). Model B is specified with identical explanatory variables as Model A. The test is as follows:

$$\left(\hat{b}_r - \hat{b}_u\right)' \left[\hat{V}_r - \hat{V}_u\right]^{-1} \left(\hat{b}_r - \hat{b}_u\right) = c^2$$

distributed with $\tilde{K}$ degrees of freedom, where $\tilde{K}$ is the number of elements in the subvector of coefficients that is identifiable from the restricted choice model, *r* is the restricted model, and *u* is the unrestricted choice model.

The resulting test statistic is larger than the critical value of chi-squared at a 5% level of significance and thus rejects the hypothesis that IIA holds for all four fuel choices.

Small and Hsiao (1985) show that the *Hausman test* may be unstable under certain conditions. They propose a *log likelihood ratio test* that would perform better. I now describe this test. First, randomly divide the full sample into two asymptotically equal subsamples, A and B. Then, attain two estimates of the coefficient vector from subsamples A and B with the full choice set, as $\hat{b}_C^A$ and $\hat{b}_C^B$. Next, compute a convex combination of $\hat{b}_C^A$ and $\hat{b}_C^B$. as follows:

$$\hat{b}_C^{AB} = \left(1/\sqrt{2}\right)\hat{b}_C^A + \left(1 - 1/\sqrt{2}\right)\hat{b}_C^B \quad .$$

Finally, calculate two log likelihood functions, one by using $\hat{b}_{C}^{AB}$ over subsample B, and one by using an estimate of the coefficient vector with the restricted choice set over subsample B, as $\hat{b}_{\tilde{C}}^{B}$, where $\tilde{c}$ consists of CNG, methanol, and gasoline choices only. The test statistic is then formulated as follows:

$$-2\left[L_{\tilde{C}}^{B}\left(\hat{b}_{C}^{AB}\right)-L_{\tilde{C}}^{B}\left(\hat{b}_{\tilde{C}}^{B}\right)\right]\approx c_{k}^{2} \ .$$

Following this procedure, I estimate the test statistic. This test also rejects the null hypothesis that IIA holds.

I also performed a simple log-likelihood test presented by Hausman and McFadden (1984). This test is as follows:

$$-2\big(LL(ModelA)-LL(ModelB)\big)\approx c_{(k)}^{2} \, .$$

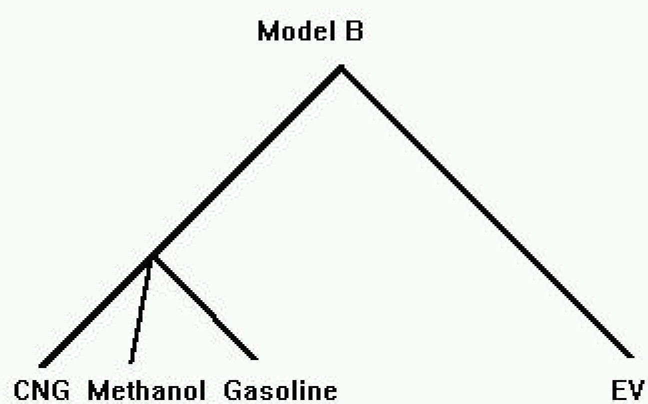
This test also rejected the hypothesis that IIA holds.

Table 5b

Model Specification Tests

Null and Alternative Hypotheses	Test Statistic Value	Critical Value of Chi-Squared (95 %)	Conclusion
Hausman Test: H_0 = Model A is superior to Model B	92.8	32.67 (k=21)	H_0 is rejected
Small and Hsiao Likelihood Ratio Test: H_0 = Model A is superior to Model B	454.57	32.67 (k=21)	H_0 is rejected
Simple Log Likelihood Test: H_0 = Model A is superior to Model B	125.88	23.69 (k=14)	H_0 is rejected

FIGURE 2



4.4 Nested Logit Models

The tests performed in the previous section suggest that a nested model such as Model B may be a better specification for the fuel choice model than a multinomial logit model. I now describe the theoretical background for nested models. I follow Train (1989, Chapter 4, pp. 65-70) in this section. In nested models, the limiting assumption of Independence from Irrelevant Alternatives (IIA) is relaxed such that all relations among probabilities can be described as follows: The ratio of probabilities on any two alternatives within the same subset is independent of the existence of other alternatives; however, the ratio of probabilities of two alternatives from different subsets is not independent of the existence of other alternatives. Thus, IIA holds within subsets but not across subsets. Hence, I assume that IIA holds among CNG, methanol, and gasoline choices, but not between any of these choices and electric vehicle choice. In other word, I assume that respondents view electric vehicles as a choice which contains some attributes that are not described in the attribute list when choosing a vehicle. These unspecified attributes set electric vehicles apart from other fuel type vehicles collectively. I believe some of these attributes may be (1) unfamiliarity with electric vehicles technology, (2) unfamiliarity with how the battery infrastructure would be operative, (3) uncertainties involved with the operation, range limitations, and other technological attributes, and (4) fear of electrocution!

I here use Train (1986, Chapter 4) to describe nested models. Assume that the set of alternatives J_n is divided into K subsets denoted by $B_n^1, \ldots, B_n^K$. I can write the utility function for person n from alternative i as $U_{in} = V_{in} + e_{in}$, where V_{in} is the indirect utility function which is observed by the researcher and e_{in} is the unobserved part of the utility. The model is obtained by assuming a generalized extreme value (GEV) distribution for e_{in}s in J_n. Thus, the joint cumulative distribution of the random variables e_{in}, for all i in J_n, is assumed to be

$$\exp\left\{-\sum_{k=1}^{K} a_k \left(\sum_{i\in B_n^k} \ell^{-e_{in}/l_k}\right)^{l_k}\right\}.$$

This distribution is the generalized form of the distribution assumed for the logit model. The difference is that here all random variables e_{in} within each node (or sub-branch of the tree) are correlated with each other. The parameter l_k represents a measure of the correlation of unobserved utility within node B_n^k. McFadden (1978) shows that the above distribution of the random component of utility yields the following choice probability for alternative i in subset B_n^k:

$$P_{in} = \frac{e^{V_{in}/\lambda_k}\left(\sum_{j\in B_n^k} e^{V_{jn}/\lambda_k}\right)^{\lambda_k - 1}}{\sum_l \left(\sum_{j\in B_n^l} e^{V_{jn}/\lambda_l}\right)^{\lambda_l}}.$$

This generalized choice probability model is called GEV. It reduces to the familiar logit model when $\lambda_k = 1$. A simple way of decomposing this probability choice model is as follows:

$$P_{in} = P_{in|B_n^k} \cdot P_{B_n^k}.$$

$P_{in|B_n^k}$ is the conditional probability of choosing alternative i given that an alternative in node B_n^k is chosen. $P_{B_n^k}$ is the marginal probability of choosing an alternative in each node. Using the above GEV model for P_{in}, I can write the marginal and conditional probabilities as follows:

$$P_{in|B_n^k} = \frac{e^{Y_{in}^k}}{\sum_{j \in B_n^k} e^{Y_{jn}^k}}, \text{ and}$$

$$P_{B_n^k} = \frac{e^{W_n^k + \lambda_k I_k}}{\sum_{l=1}^{k} e^{W_n^l + \lambda_l I_l}},$$

where $I_k = \ln \sum_{j \in B_n^k} e^{Y_{jn}^k}$.

The term I_k is called the "inclusive value" and represents the average utility that a person can get from alternatives within node *k*.

CHAPTER 5

FUEL CHOICE MODELS AND RESULTS

5.1 Conditional Multinomial Logit And Nested Logit Estimation Results

I estimate and present the nested logit model of fuel choice with industry types, fleet size, vehicle body type, vehicle duty cycle, on-site refueling availability, and stated choice variables entered as explanatory variables. Although the specification tests in section 4.2 suggest that the nested logit Model B might be a better specification, the resulting choice probabilities generated from both Model A and Model B turn out to be almost identical. Since there are repeated responses due to the Stated Preference scenarios,[14] there could be correlation problems which would be problematic with a nested model.[15] Also, for forecasting purposes, the use of the multinomial logit model rather than a nested logit model eases the computation while it does not alter the predicted choice probabilities. I show both the multinomial logit model and the nested logit model in Table 6. However, I use the multinomial logit model for most of my analysis hereafter.

For the nested model, I employ a sequential nested estimation procedure.

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[14] In fact, each SP scenario response is expanded into nine records to account for the conditional nature of the choices and that each respondent could choose up to three choices.
[15] One way of correcting this problem could be to use a Random Parameter Model as described by Revelt and Train (1996).

Table 6

Models A and B

DESCRIPTION	Model A Multinomial Logit		Model B Nested Logit	
Base choice = gasoline vehicle	Coef.	t	Coef.	t
EV constant (all observations)	-0.686	-1.78	-1.133	-3.44
EV constant * [SP vehicle body type = compact pick up]	0.307	2.28	0.290	2.19
EV constant * [SP vehicle function = service/maintenance calls]	0.342	3.18	0.342	3.23
EV constant * [organization type = schools]	0.776	4.19	0.827	5.54
EV constant * [organization type = agriculture related firms]	-0.655	-1.88	-0.767	-2.27
EV day-time recharging cost, cents/mile.	-0.015	-1.53	-0.013	-1.27
EV on-site refueling time in hours.	-0.066	-1.58	-0.067	-1.65
EV service station recharging time in minutes	-0.004	-1.48	-0.005	-1.70
EV * Capital cost of vehicle for all firms but those in construction industry.	-0.056	-1.62	-0.170	-3.61
EV * capital cost * [organization type = construction firms]	-0.087	-1.53	-0.117	-2.06
EV * range	-0.001	-0.53	0.002	1.41
EV * range * [SP vehicle function = transport / shuttle people]	0.003	1.93	0.006	3.86
EV * [# of refueling stations relative to gasoline stations]	-0.709	-2.10	-0.329	-1.11
EV cargo capacity compared to gasoline vehicles	0.038	0.17	0.019	0.08
CNG constant (all observations)	-0.469	-2.74	-0.409	-2.29
CNG constant * [organizations with fleet site size of at least 120 vehicles]	0.420	3.01	0.470	3.14
CNG constant * [organization type = city and county agencies]	0.310	2.43	0.415	2.89
CNG constant * [organization type = schools]	0.443	2.73	0.550	3.14
CNG constant * [organization type = retail and wholesale firms]	-0.254	-1.46	-0.294	-1.64
CNG constant * [organization type = banking, insurance and real estate]	-0.735	-1.90	-0.778	-1.96
CNG dual fuel capability: 0 = CNG only; 1 = can also run on gasoline.	0.293	3.57	0.304	3.53

Table 6 (continued)

Models A and B

DESCRIPTION	Model A Multinomial Logit		Model B Nested Logit	
Base choice = gasoline vehicle	Coef.	t	Coef.	t
CNG service station refueling time in minutes	-0.026	-2.53	-0.027	-2.53
CNG cargo capacity compared to gasoline vehicles	0.182	1.40	0.116	0.85
Methanol constant (all observations)	-0.194	-2.05	-0.179	-1.83
Methanol constant * [organization type = schools]	-0.297	-1.71	-0.228	-1.26
Methanol constant * [organization type = transportation/ communication]	-0.275	-1.69	-0.292	-1.71
Methanol constant * [organization type = agriculture related firms]	0.343	1.85	0.363	1.92
Gasoline on-site refueling available	0.272	3.54	0.318	3.76
Capital cost of vehicle for all but those firms in construction industry.	-0.231	-4.83	-0.308	-5.24
Capital cost * [organization type = construction firms]	-0.128	-1.17	-0.022	-0.18
Vehicle range in miles interacted with all observations <u>excluding</u> those with SP vehicle function = transport/shuttle people.	0.002	6.04	0.002	6.14
Vehicle range * [SP vehicle function = transport / shuttle people]	0.001	2.33	0.001	2.08
# of refueling stations relative to gasoline stations	0.316	2.99	0.351	3.24
Operating cost in cents/mile (CNG, methanol, gasoline)	-0.059	-5.07	-0.061	-5.05
Tailpipe emission * [organization type = a city/county agency or a school]	-0.396	-2.60	-0.176	-0.93
Lambda: coefficient of the inclusive value			0.291	2.06

Dependent variable = vehicle choice.
Choices = Three out of four possible choices of electric vehicle (EV), compressed natural gas vehicle (CNG), methanol vehicle, and gasoline vehicle.
Number of observations: expanded version 12675.
Coefficient estimates reported in the Nested Model B for CNG, Methanol, and Gasoline interactions are actually b/λ .

Table 7

Mean Values of the Covariates

Variable	Mean	Std. Dev.	Min	Max
EV constant (all observations)	0.2512	0.4337	0	1
EV constant * [SP vehicle body type = compact pick up]	0.0360	0.1862	0	1
EV constant * [SP vehicle function = service/maintenance calls]	0.1184	0.3231	0	1
EV constant * [organization type = schools]	0.0228	0.1493	0	1
EV constant * [organization type = agriculture related firms]	0.0110	0.1041	0	1
EV day-time recharging cost, cents/mile.	3.3370	6.2895	0	20
EV on-site refueling time in hours.	1.0817	1.9665	0	6
EV service station recharging time in minutes	9.1479	17.9720	0	60
EV * Capital cost of vehicle for all firms but those in construction industry.	0.5267	1.3100	0	12
EV * capital cost * [organization type = construction firms]	0.0857	0.5611	0	7
EV * range	20.0316	43.7709	0	150
EV * range * [SP vehicle function = transport / shuttle people]	5.8351	25.4470	0	150
EV * [# of refueling stations relative to gasoline stations]	0.0662	0.1419	0	0.5
EV cargo capacity compared to gasoline vehicles	0.0164	0.1161	0	1
CNG constant (all observations)	0.2463	0.4309	0	1
CNG constant * [organizations with fleet site size of at least 120 vehicles]	0.0281	0.1652	0	1
CNG constant * [organization type = city and county agencies]	0.0386	0.1926	0	1
CNG constant * [organization type = schools]	0.0240	0.1530	0	1
CNG constant * [organization type = retail and wholesale firms]	0.0155	0.1237	0	1
CNG constant * [organization type = banking, insurance and real estate]	0.0053	0.0725	0	1
CNG dual fuel capability: 0 = CNG only; 1 = can also run on gasoline.	0.1087	0.3113	0	1
CNG service station refueling time in minutes	2.4840	4.7889	0	15
CNG cargo capacity compared to gasoline	0.1500	0.3099	0	0.85

Mean Values of the Covariates

Variable	Mean	Std. Dev.	Min	Max
vehicles				

Table 7 (continued)

Mean Values of the Covariates

Variable	Mean	Std. Dev.	Min	Max
Methanol constant (all observations)	0.2490	0.4324	0	1
Methanol constant * [organization type = schools]	0.0234	0.1510	0	1
Methanol constant * [organization type = transportation/ communication]	0.0165	0.1274	0	1
Methanol constant * [organization type = agriculture related firms]	0.0103	0.1008	0	1
Gasoline on-site refueling available	0.1128	0.3164	0	1
Capital cost of vehicle for all but those firms in construction industry.	1.9420	1.7227	0	12
Capital cost * [organization type = construction firms]	0.3346	1.0800	0	7
Vehicle range in miles interacted with all observations excluding those with SP vehicle function = transport/shuttle people.	149.7846	112.2882	0	350
Vehicle range * [SP vehicle function = transport / shuttle people]	42.9629	90.7126	0	350
# of refueling stations relative to gasoline stations	0.5013	0.3522	0.1	1
Operating cost in cents/mile (CNG, methanol, gasoline)	7.4978	4.6142	0	13
Tailpipe emission * [organization type = a city/county agency or a school]	0.0823	0.2039	0	1

Table 8

Average Predicted Probabilities of Fuel Choice From Model A

	All Observations	Large Fleets
Electric Vehicle	0.12	0.13
Compressed Natural Gas Vehicle	0.21	0.28
Methanol Vehicle	0.24	0.19
Gasoline Vehicle	0.43	0.40

To get an idea of the implied choice probabilities that Model A generates for specific fleets, I calculate the probabilities of choosing a vehicle with four representative cases composed of mean values of the attributes and for vehicle body type = "cars and station wagons", vehicle function = "transporting / shuttling people". I assume that on-site refueling is available for gasoline, and that there is no dual fuel capability for CNG vehicles. In the first two cases, I compare the resulting probability choices of two fleet sites with less than 120 vehicles from two distinct industry groups. In Cases 3 and 4, I repeat the choice probability calculations given the same set of assumptions as the previous cases except this time I choose only large fleets in my case studies. Cases 1 & 3 are for "city and county agencies" only. Cases 2 & 4 are for "construction firm". I summarize the results in Table 9. All these cases yield distinct results: "city and county" agencies choose more CNG vehicles relative to other fuel types than do construction fleets in both small and large fleet cases. This supports the argument that public and private agencies differ in their AFV choice.

Table 9

Four Cases of Vehicle Fuel Choice Probabilities
From Model A

Vehicle Fuel Types	***Case 1 City/County Agencies Small Fleets***	***Case 2 Construction Firms Small Fleets***	***Case 3 City/County Agencies Large Fleets***	***Case 4 Construction Firms Large Fleets***
EV	0.17	0.14	0.15	0.13
CNG	0.32	0.19	0.41	0.26
Methanol	0.19	0.21	0.17	0.19
Gasoline	0.32	0.46	0.27	0.42

I calculate the tradeoff between capital cost of the vehicles and the range of the vehicles for different industry subgroups in the sampled fleet sites (Table 10). My motivation to do so was to get an idea of the valuation the fleet managers place on the limited range of the AFVs. The value of an additional mile range turned out to be about $81 for all firms combined. This value is considerably higher than the estimate of $1.03 given by Shonka (1980). I calculate the implied values of interest rate of the operating cost with respect to the capital cost that my model generated. They appear to be reasonable. That is, assuming an annual vehicle mileage of 25,000, the implied interest rate is calculated at 11%, and assuming an annual vehicle mileage of 18,000, it turns out to be 8%.

Table 10

Range/Capital Cost Tradeoffs From Model A

Fleet Subgroup	$ Willing To Pay For Each Additional Mile Range
General case	$81
City and county agencies	$14
Construction and contracting industry	$166
Manufacturing industry	$101
Agriculture industry	$105
Transportation and communication industry	$83
Banking, insurance, and real estate industry	$41
Schools (both private and public)	$53
Business services	$84

The capital cost / range tradeoff values are very different for some industry groups: “city and county” agencies have a tradeoff value of $14, while for firms in the “construction or contracting” business the value rises to over $160. Range in general is confirmed to be an important factor in vehicle choice. Nevertheless, these results show the wide variation that exits in perceiving the importance of range between different segment of fleets.

5.2 Forecasting

I construct a set of forecasting weights from a schedule of vehicle types taken directly from the Department of Motor Vehicles' (DMV) records of all vehicles in California. Since the number of records were extremely high, a random sample was taken from them consisting of 1.8 million records. A complicated algorithm, then, was implemented to distinguish between commercial vehicles and residential ones. Then, the frequency of vehicles in each body type for the commercial fleet section was calculated. The weights that I use are constructed from these frequency counts. The frequency table for vehicle body types is reported in Table 11.

Table 11

Vehicle Count by Fleet Vehicle Body Type

Vehicle Body Type	***Estimated Count from the 1.8 million record sample***	***Fleet Survey Sample Count***
Mini	5039	83
Subcompact	19356	321
Compact	37635	623
Mid-size	56366	933
Full-size	15360	254
Luxury	14873	246
Sport	25125	416
Compact Pick-ups	36689	909
Full Size Pick-ups	120970	1560
Minivans	15022	1815
Full vans	64245	3705
Trucks (<= 14,000 Ibs)	21923	1809

I use the weighted predicted probabilities of fuel choices for forecasting purposes. Previously I have estimated the probabilities of each fuel choice with Model A for the stated preference attribute levels. The attribute levels in the stated choice scenarios, however, do not represent the real technology levels. Thus, from Model A, I calculate the probability choices assuming the technology levels that are expected to be available to consumers for the year 2010. These technology levels are described in Appendix II. The resulting probability forecasts represent long-term choice probabilities. From these figures, then, one can calculate estimates for the long-term EV, CNG, and methanol vehicle demand by applying these probabilities to the total number of vehicles projected to be demanded in the year 2010.

Table 12

Predicted Vehicle Fuel Choice Probabilities
For Year 2010

Vehicle Type	*Choice Probabilities*
Electric Vehicle	0.17
Compressed Natural Gas Vehicle	0.20
Methanol Vehicle	0.21
Gasoline Vehicle	0.42

The above AFV forecasting probabilities are considerably higher than shares predicted by Kazimi (1996), who reports total market penetration predictions for household vehicles. For example, Kazimi (1996) predicts a 6% new vehicle market penetration for electric vehicles, 13% for CNG vehicles, and 18.2% for methanol vehicles in year 2008. I predict substantially higher (17%) percentage of new purchases for the electric vehicles by commercial fleets. I also predict a 7% more share for CNG and a 3% more share for methanol vehicles than Kazimi (1996). This is consistent with my earlier discussion that commercial fleets are more likely to be the first purchasers of alternative fuel vehicles than households. Especially for less familiar alternative fuel vehicle technology such as EV or CNG, these divergence's of household-based predictions and commercial fleet-based predictions are consistent with the expectation.

CHAPTER 6

EXTENSIONS OF FUEL CHOICE MODELS

6.1 Categorizing the data by Market Structures

So far, I have demonstrated the overall AFV market shares for the next fifteen years. But, we still do not know how these probabilities vary across different types of organizations. In order to study the effect of market organizations on the fuel choice, I extend Model A by adding some other important covariates and estimating separate models for each market segment. I develop several categories of market structure by combining some of the industry categories. The motivation for this segmentation was to understand possible similarities or differences that exist between private, public, and regulated industries. The market structure groups are (1) Public Schools, (2) Private Schools, (3) Firms which have rate-of-return regulations, such as utility companies and insurance companies, (4) high-technology firms which are military contractors, (5) public agencies, (6) private firms, and (7) hospitals.

I estimate my vehicle choice model for each of these seven segments separately and then perform a series of Log-Likelihood tests comparing pooled models with separate segment models. The Log-Likelihood tests fail to reject the hypothesis that *hospitals* category pooled with the *public firms* category. By the same token, *high-tech firms* are not distinguishable from other *private firms.* I also test and reject the hypothesis that *public schools* behave like *public firms.* I could not determine where *private schools* should be pooled. I test the hypothesis that *private schools* can be pooled with other *private firms*. The test rejects that hypothesis. The hypothesis that *private schools* and *public schools* behave similarly in my models is also rejected. Since I had a few records in the *private schools* category, I decided not to make *private schools* a separate segment rather I included those records in the *All Fleets* model which is an estimate of the model using all records in the data set. I ended up with four distinct market structure segments and a generic category of *All Fleets*. Table 13 shows the frequency of the fleet sites, the percentages of total fleet sites and the average fleet sizes for these different market segments.

Table 13

Fleets' Market Segments

Market Segments	***# of Fleet Sites***	***% of Total Fleet Sites***	***Average Fleet Size***
Public Schools	179	8.4	71
Rate-of-return regulated firms	90	4.22	170
Public agencies (city and county only)	296	13.89	179
Private firms	1445	67.81	36
Private schools, high-tech firms, hospitals, and unknown categories	121	5.68	93

6.2 Vehicle & Firm Characteristics by Market Segments

Tables 14 through 18 provide some additional descriptive statistics for these market segments. The most popular vehicle body type[16] by firms overall, as well as for public schools, public entities, and private entities, are full-size pickups, followed by cars and station wagons. The largest vehicle body type of the rate-of-return regulated firms is "cars and station wagons"; the second largest type is "minivans". Note that we have gathered detailed information on only two types of fleet vehicles. If a particular vehicle fleet was composed of more than two types of vehicles, we chose the largest type and we randomly selected one vehicle type out of the remaining vehicles and gathered detailed data on that vehicle type. Thus, in these tables, I am referring to at most two types of fleet vehicles only.

Both private and public organizations indicated that their vehicles are used mostly for "service and maintenance calls". The second most frequent function of fleet vehicles was "haul equipment" category for private firms and "employee use" for public entities. "Employee use" is also one of the most important vehicle functions for regulated firms. Vehicles used for employees constituted over 22% of all surveyed SP vehicles and this is mostly due to public entities and regulated firms.

We included a question in the survey asking the fleet managers whether or not they believed that they were subject to AFV regulation. Over 31% of all firms said they believed they are subject to regulation on their fleet vehicle emission. Fleet managers generally know all regulations affecting their vehicles, and there is no reason to believe that they would

[16] Note that this is solely based on the vehicles in the stated preference scenarios.

misrepresent their organization's regulatory state. Therefore, I treat the fleet managers' responses to the AFV regulation question as objective answers.

Overall, 17.9% of all firms in the sample currently have AFVs, but only 12% of private firms currently have AFVs while 38% of public entities and 21% of public schools have AFVs. Surprisingly, only 11% of rate-of-return regulated firms (which includes utility companies) have AFVs. This low figure may be due to including insurance companies in the category. Almost 65% of firms with the AFV regulation have at least one hundred employees. But only 27.34% of private firms have at least one hundred employees.

<u>**Table 14**</u>

Fleet Vehicle Body Type Composition

() Row percentages. Example: 5.44% of “cars & station wagons” are owned by “public Schools” in the data.
<> Column percentages. Example: 23.24% of all vehicles were “cars & station wagons”.

	All	***Public Schools***	***Public Entities***	***Regulated Firms***	***Private Firms***
Cars & Station Wagons	3420 <23.24>	189 (5.44%) <13.73>	750 (21.93%) <30.41>	228 (6.67%) <37.81>	1995 (58.33%) <21.21>
Minivans	1068 <7.26>	60 (5.62) <4.36>	126 (11.8) <5.11>	105 (9.83) <17.41>	660 (61.8) <7.02>
Full-size vans	1860 <12.64>	291 (15.65) <21.13>	183 (9.84) <7.42>	75 (4.03) <12.44>	1116 (60.0) <11.87>
Compact pick-ups	2079 <14.13>	159 (7.65) <11.55>	384 (18.47) <15.57>	60 (2.89) <9.95>	1410 (67.82) <14.99>
Full size pick-ups	3966 <26.95>	471 (11.88) <34.20>	660 (16.64) <26.76>	84 (2.12) <13.93>	2595 (65.43) <27.59>
Buses	219 <1.49>	63 (28.77) <4.58>	57 (26.03) <2.31>	0 (0) <0>	78 (35.62) <0.83>
Trucks	2106 <14.31>	144 (6.84) <10.46>	306 (14.53) <12.41>	51 (2.42) <8.46>	1551 (73.65) <16.49>
Column Subtotals	14,718	1,377 (9.36)	2466 (16.75)	603 (4.1)	9405 (63.9)

Table 15

Fleet Size by Market Structures

() Row percentages <> Column percentages

	All Fleets	***Public Schools***	***Public Entities***	***Regulated Firms***	***Private Firms***
Fleets of at least 120 vehicles	1923 <13.07>	243 (12.64) <17.65>	957 (49.77) <38.81>	66 (3.43) <10.95>	471 (24.49) <5.01>

Table 16

Employee Size

() Row percentages <> Column percentages

	All Fleets	***Public Schools***	***Public Entities***	***Regulated Firms***	***Private Firms***
Employee size of at least 100	5379 <36.55>	774 (14.39) <56.21>	1059 (19.69) <42.94>	393 (7.31) <65.17>	2571 (47.8) <27.34>

Table 17

Current Users of AFV

() Row percentages <> Column percentages

	All Fleets	***Public Schools***	***Public Entities***	***Regulated Firms***	***Private Firms***
Currently has AFV	2631 <17.88>	288 (10.95) <20.92>	948 (36.03) <38.44>	69 (2.62) <11.44>	1167 (44.36) <12.41>

Table 18

Vehicle Duty Functions

Note that these vehicles are only those vehicle body types that we have collected *Stated Preference* data on. Also note that each vehicle may have more than one duty function.

() Row percentages <> Column percentages

	All	***Public Schools***	***Public Entities***	***Regulated Firms***	***Private Firms***
Courier, Pick Up, And Delivery	3057 <14.03>	147 (4.81) <7.56>	156 (5.10) <4.35>	24 (0.79) <2.83>	2478 (81.06) <17.44>
Haul Equipment	3696 <16.97>	243 (6.57) <12.50>	408 (11.04) <11.37>	96 (2.60) <11.31>	2841 (76.87) <20.00>
Shuttle People	3306 <15.17>	381 (11.52) <19.60>	699 (21.14) <19.48>	72 (2.18) <8.48>	1875 (56.72) <13.20>
Service & Maintenance Calls	6894 <31.64>	942 (13.66) <48.46>	1398 (20.28) <38.96>	339 (4.92) <39.93>	3969 (57.57) <27.94>
Sales	1545 <1.09>	0	42 (2.72) <1.17>	120 (7.77) <14.13>	1269 (82.14) <8.93>
Employee Use	3288 <15.09>	231 (7.03) <11.88>	885 (26.92) <24.67>	198 (6.02) <23.32>	1773 (53.92) <12.48>
Column Totals	21,786	1944 (8.92)	3588 (16.47)	849 (3.90)	14205 (65.20)

6.3 Models of Choice Partitioned by Organization Types

In addition to partitioning the fuel choice model by the market structure categories, I added some new covariates that may shed some more light in the understanding of market structures and AFV choice behavior. These covariates were chosen based on the lessons learned from the technology diffusion literature. The added covariates are as follows: a dummy for large number of employees, a dummy for current or past experience with AFVs, and a dummy for current AFV regulation affecting the firm. Table 19 shows the estimation results for these models.

6.4 Firm Size

In the diffusion literature, firm size has been cited as one important factor in the adoption of a new technology. Fleet size could partially proxy for the firm size, but a more complete study of the effect of size in the diffusion would include other measures of firm size such as "number of employees" or "gross annual revenue". The data set contained information on the former but not on the latter. In addition to the dummy variable for the fleet size, I made a dummy variable with a value of one for firms that have at least one hundred employees. The coefficient of the interaction of this variable with fuel choice dummies confirms that larger firms are more likely to choose AFVs, even holding the fleet size constant. An example of this is the interaction of the employee-size dummy variable with the CNG dummy which is significant and positive for firms overall. This is consistent with the technology diffusion literature prediction that larger firms are more likely to adopt new technology.

6.5 Learning by Doing

Another important factor cited by diffusion literature affecting new product adoption is the degree of past exposure and experience with the product. As the product gets used, people gain experience and familiarity with unique characteristics of the new product. This learning process is thought to be a crucial factor in the success of new products. A product that is very different in some aspects from the one it aims to replace is harder to sell. That is why offering free training or free sampling of an unfamiliar product is often used as a marketing strategy. In the survey, the respondents were asked to indicate whether they currently have at least one AFV in their fleet. A dummy variable with value of one for current AFV user was included in the set of covariates. The interaction of “AFV experience” with the fuel choice dummies confirms the crucial effect of learning by doing and experience in the adoption of AFVs.

6.6 Government Regulation

Government regulation may be necessary for the diffusion of AFVs given that currently consumers are not penalized for their vehicle emissions. But how important is government regulation? A question was included in the survey which asked the respondents whether or not they believed their fleet was subject to emission regulation. I construct a dummy variable with the value of one if the responses were positive. Interaction of this variable with the fuel dummies confirms the important effect of regulation. For both EV and CNG, which are technologically very different from conventional gasoline vehicles and thus encounter more resistance by consumers, these coefficients are positive and significant. For methanol, however, it does not have a significant effect. Only in the case of public schools does government regulation of emissions exhibit a negative effect on the choice of methanol vehicles. This may reflect some concern regarding methanol's safety.

6.7 Infrastructure

The technology diffusion literature emphasizes that networking externalities affect the diffusion process. Infrastructure of service stations and supporting refueling facilities fall into this group of externalities for AFV diffusion. A higher ratio of AFV service stations to gasoline stations would mean a higher level of in-place infrastructure and thus higher likelihood of AFV adoption. The results of my models confirm this argument. Service station availability has a positive effect on the AFV choice over all sampled firms. The following example may further illustrate this argument. Suppose that there were a 20% increase in the number of AFVs. We can expect that there would be some increase in the number of service stations that offer AFVs. Let's assume that an extra 10% of gasoline stations now offer alternative fuels. The forecasting probabilities for AFVs, as predicted by Model A, are going to increase as follows: electric vehicles' market share would increase to

19%, CNG's market share would increase to 22%, and methanol's market share would increase to 22%, generating an overall 5% increase in the AFV market share.

Table 19

Conditional Logit Models Of Fuel Choice Partitioned By Organization Types

(Note: nonsignificant variables are not shown but are included in the model)
Dependent variable = vehicle choice
Number of choices = Three out of four possible choices of electric vehicle (EV), compressed natural gas vehicle (CNG), methanol vehicle, and gasoline vehicle.
Base choice = gasoline vehicle
Values in the parenthesis are coefficients' t-statistics.
Table of mean, standard deviation, minimum, and maximum values for all these models' covariates are presented in Appendix III.

Variable Description	*All Firms*	*Public Schools*	*Public Agencies*	*Regulated Firms*	*Private Firms*
EV constant	-1.183 (3.3)				-0.976 (2.1)
EVconstant*fleet size >=120		4.979 (2.6)	-1.769 (1.9)		-2.248 (2.0)
EVconstant* compact pick ups	0.257 (2.1)		0.646 (2.6)		
EVconstant* small trucks	-0.448 (3.1)		-0.952 (2.5)		-0.320 (1.8)
EV constant * usage=maintenance	0.461 (4.6)	0.963 (2.4)			0.256 (2.0)
EVconstant*usage=shuttle	0.545 (4.8)				0.612 (4.2)
EVconstant* AFV exp.	0.354 (2.5)				0.544 (2.8)
EVconstant*regulated emission	0.187 (1.6)		0.917 (3.6)		
EV with gasoline range extender.		-0.618 (2.2)			0.206 (1.7)
CNG constant	-1.026 (5.5)	-2.352 (2.9)		-2.488 (2.3)	-0.791 (3.4)
CNG const*fleet size >= 120					
CNG const*usage=maintenance	0.168 (2.0)	0.808 (2.1)		1.071 (1.8)	
CNG const*usage=shuttle	0.181 (1.8)	0.623 (1.6)	0.536 (2.4)		

Variable Description	***All Firms***	***Public Schools***	***Public Agencies***	***Regulated Firms***	***Private Firms***
CNG const*employees>= 100	0.176 (1.9)			1.318 (1.9)	

Table 19 (continued)

Conditional Logit Models Of Fuel Choice Partitioned By Organization Types

Variable Description	***All Firms***	***Public Schools***	***Public Agencies***	***Regulated Firms***	***Private Firms***
CNG const*regulated emission	0.321 (3.3)		0.602 (2.7)	1.087 (1.8)	
CNG dual capability	0.214 (2.8)	0.577 (2.4)			0.261 (2.7)
Methanol constant		-0.960 (1.8)	0.578 (1.9)		
Meth const*fleet size >=120	-0.433 (1.4)				
Meth const*employees>= 100				-0.786 (1.6)	
Meth const* AFV exp.	0.275 (2.3)	0.944 (2.1)			0.341 (2.2)
Meth const*regulated emission		-0.563 (1.7)		1.452 (2.4)	
Capital cost ($10,000)	-0.211 (5.0)			-1.145 (2.7)	-0.258 (5.0)
Capital cost*fleet size >=120 ($10,000)			-0.342 (1.7)		
Range (10 miles)	0.021 (6.8)				0.026 (6.8)
Range*fleet size >119	-0.024 (2.5)			0.241 (1.8)	-0.051 (2.8)
Tailpipe emission		-0.498 (1.6)			
Tailpipe emission*fleet size >119		2.882 (3.1)			
Service station availability	0.237 (2.7)		0.657 (3.3)		0.189 (1.7)
Similar vehicles on road (10,000)		0.035 (1.8)			
Operating cost (non-EV)	-0.054 (4.6)				-0.069 (5.0)
Operating cost*fleet size >119			-0.128		

Variable Description	***All Firms***	***Public Schools***	***Public Agencies***	***Regulated Firms***	***Private Firms***
			(2.3)		

Table 19 (continued)

Conditional Logit Models Of Fuel Choice Partitioned By Organization Types

Variable Description	*All Firms*	*Public Schools*	*Public Agencies*	*Regulated Firms*	*Private Firms*
EV day recharge cost (cents)		-0.174 (2.4)			0.119 (2.3)
EV day recharging*fleet size >119	-0.018 (1.8)				-0.025 (2.0)
CNG slow fill unit cost	0.129 (2.6)		0.234 (2.3)		0.117 (1.8)
Methanol on-site pump cost	-0.087 (2.4)		-0.224 (2.0)	-0.879 (3.5)	
Meth pump cost*fleet size >119		1.195 (1.8)		2.098 (1.8)	
Gasoline on-site pump dummy	0.224 (3.0)		0.317 (1.7)		0.366 (3.8)
CNG fastfill unit cost ($10,000)	-0.037 (2.8)		-0.064 (2.0)		-0.036 (2.2)
EV on-site charge time hrs: 3,4,6	-0.054 (1.5)				-0.085 (1.7)
EV refueling time at station min: 20,30,60	-0.007 (2.6)			-0.037 (1.6)	-0.011 (3.0)
Cargo capacity (EV and CNG)	0.203 (1.8)		0.714 (2.8)	1.020 (1.6)	

SUMMARY AND CONCLUSION

In Part I of this dissertation, I construct multinomial conditional and nested logit fuel choice models that predict the market share of alternative fuel vehicles in the next fifteen years for commercial and local government fleets in California. My data set consists of *stated preference* data as well as data on the firm and vehicle characteristics for over 2000 commercial establishments and local governments. This is the most comprehensive alternative fuel vehicle data set for the commercial fleets to date. The *stated preference* questionnaire describes up to two distinct experiments consisting of three vehicle scenarios customized to fit the attribute set of vehicle body types in the firm's vehicle fleet. I utilize the lessons from both transportation literature and new technology diffusion literature to establish the covariates for the fuel choice models. My models forecast a 17% new vehicle market share for electric vehicle by the commercial fleets by year 2010, a 20% new purchase share for CNG vehicles, and a 21% share for the methanol vehicles.

These results suggest that for the light duty commercial fleets, we can expect a substantial diffusion of alternative fuel vehicles under the assumed technology levels by the year 2010. However, we still do not know how that would affect the diffusion of alternative vehicles into the total vehicle population which consists primarily of the household vehicles. Studies such as Kazimi (1996) and Ren, et al (1995) shed light on the likely household demand for alternative fuel vehicles. But, we still do not know how a substantial AFV diffusion into the commercial fleets may impact the household sector by creating a networking effect: (1) As the commercial establishments use more AFVs, we expect to see an increase in the level of overall familiarity with the new technology. (2) As the commercial establishments use more AFVs, we expect to see an improved AFV infrastructure level. In Chapter 6, I showed how these networking effects might change the fuel choices of the commercial fleets' survey respondents and how that varies in different types of market organizations. Environmental impact studies could use my predictions of the AFV diffusion for the commercial fleet segment of the market, as well as household market predictions from other studies, and evaluate the overall impact of AFV adoption on the emission levels.

PART TWO

PUBLIC CHOICE ISSUES

CHAPTER 7

EFFICIENCY IN PUBLIC ORGANIZATIONS: A CASE STUDY

7.1 INTRODUCTION

7.1.1 Background

Some public choice scholars contend that the public sector operates less cost efficiently than the private sector. Government productivity studies show that government productivity is less than private sector productivity and it may even be zero or negative. (Pommerehne and Schneider, 1982) A private firm would close when its costs exceed its revenues for an unreasonable length of time. A public agency, on the other hand, is not necessarily accountable for its product's cost efficiency, (Johnson and Libecap, 1994) and frequently its budget is not directly related to its productivity. Empirical studies have also found results consistent with these theories. Mueller (1989, Table 14.1) summarizes studies that compared the provision of similar services by public and private firms. Most of these studies find public firms to be significantly less efficient than private firms supplying the same services. The theories offered by the scholars posit the following major attributes of public agencies as the characteristics that lead the agencies to more wasteful behavior than competitive firms: (1) the monopoly power of public agencies, (2) the unmeasurable nature of their products, and (3) the inherent double principal-agent problem between the citizen and the politician, and between the politician and the bureaucrat. (Mueller, 1989; Wolf, Jr., 1993; Niskanen, 1994; Johnson and Libecap, 1994).

7.1.2 Why are public agencies less efficient?

A monopoly organization is thought to be more wasteful than firms in the competitive market, because absent the competitive pressure (1) cost controls may become lax, (2) organizations may tolerate and maintain what Leibenstein (1966) calls “X-inefficiencies”, and (3) the prospect of “rent-seeking” abilities may motivate the organization to incur substantial and possible wasteful expenditures to obtain, strengthen, and defend monopoly position. (Scherer & Ross, 1990) Public agencies are in most cases monopolies providing some public good. Moreover, the cost of producing their output is usually unmeasurable and if it is measurable, it is usually measurable as a lump-sum rather than per-unit cost. Hence, it is harder to quantify the minimum cost of production at margin, and it is harder to determine the extent of cost inefficiency.

The opportunity for the existence of the principal - agent problems between the citizen and the government actors could also explain why inefficiencies exist and persist in government agencies. But, important questions still remain: Do all public agencies behave with a similar degree of inefficiency? What type of government agency is more conducive to cost inefficiencies, and why? How does the citizen/voter affect the degree of these inefficiencies? How do government organization affect the degree of wastefulness in the production of its output?

7.1.3 The Purpose of This Paper

In this paper, I address the above questions. I focus on a subset of government forms, namely local government organizations. I propose hypotheses regarding different forms of local government agencies and their relationships to cost efficiency behavior. I provide empirical analyses testing some of these hypotheses in the context of a case study. My case study consists of stated choice of one type of intermediary good, namely fleet vehicles, in the presence of alternative fuel vehicles. This experiment allows me to compare the stated choices that firms and various types of public agencies make on the basis of similar hypothetical information for an intermediate good and thus could be indicative of how other choices of products and services within organizations may be made. Choosing an intermediary good for this experiment makes it possible to compare the respondents' approaches to a common choice problem across various types of industries and various organizational modes. This is more informative than an experiment regarding a primary input choice, which is specific to a particular industry, would be. The experimental nature of the design is also a good way of standardizing and allocating product attribute levels across the respondents' given hypothetical scenarios. It reduces the problem of correlation that may arise in studies based on observed behavior (revealed choice).

7.2 LITERATURE REVIEW AND SOME INSIGHTS

7.2.1 What Types of Government Organization Are More Cost Inefficient?

According to Mueller (1989), *bureaucratic man* pursues power, *political man* pursues votes, and *economic man* pursues profit. Thus, in order to look at how public organizations behave, one must first reconcile the differences between *political man* and *bureaucratic man*. Government organizations could be dissected into two major types: those run directly by elected officials / politicians, and those run by career bureaucrats who run bureaus funded at the discretion of the politicians. The potential agency problem, then, is essentially a double principal - agent problem: the citizen - politician problem on the one hand, and the politician - bureaucrat problem on the other. Hence, we have to examine the distinctive behavior of two actors within the public sector: the politician, and the career bureaucrat. I define a politician as someone who is elected by citizen votes to preside a particular office and who can be replaced by another politician through citizen elections. A bureaucrat, on the other hand, is someone who is not elected by citizen votes to his job but is a career employee managing a bureau. Bureau, in turn, is defined here as a non-profit organization that is financed, at least in part, by a periodic appropriation or grant determined by some elected politicians.

The politician's objective is to increase votes, i.e., to keep voters and interest groups happy by appearing to be carrying out the revealed demand of the citizens / interest groups. He may also have other objectives such as increasing his personal wealth, increasing his personal leisure, and other rent-seeking goals. (Mueller, 1989, p. 247) The degree by which the citizen / voter can monitor the behavior of the politician would determine the politician's likelihood to pursue citizen's wishes or his own rent-seeking objectives.

Bureaucrats, on the other hand, are usually under less close scrutiny and are less visible than politicians. Thus, bureaucrats may be less likely to be caught if they acted inefficiently. The bureaucrats' objective function consists of salary, perquisites of the office, public reputation, power, patronage, output of the bureau, ease of making changes, ease of managing the bureau, X-inefficiencies, and risk-aversion. (Niskanen, 1971; Mueller ,1989)

7.2.2 What Are the Sources of the Citizen - Politician Agency Problem?

The principal - agent problem between the citizen/voter and the politician is due to the following factors: (1) The direct monitoring power and authority of the citizen/voter is distanced from the politician's position. Examples of the situations which are conducive to more inefficiencies are: when representative government exists, when there is no referendum power, and when citizens do not have recall power. (2) The size and complexity of the government is prohibitive for easy monitoring. Thus, larger government agencies and the more complex organizational structure of the agencies contribute to the increasing opportunity of behaving inefficiently. As a result, in the context of local governments, when the jurisdiction is larger, and there are various layers of organizational bureaucracy, it is harder for the outsiders to discover and control wasteful behavior. (3) The danger of logrolling power and agenda setting to legislate laws and promote projects that do not represent the true preferences of the voters. Weingast and Moran, (1983) present an empirical evidence on how agenda setting influences the outcome of legislation in the Congress.

7.2.3 What Are the sources of the Politician - Bureaucrat Agency Problem?

The principal-agent problem between the politician/sponsor and the bureaucrat carrying out the proposed action within a bureau is acknowledged by Niskanen (1994). He argues that the incentives of bureaucrats do not lead to behavior that is fully consistent with the interests of politicians. The problem could be due to the following: (1) the bureau has considerable monopoly power; (2) the size and complexity of the government is prohibitive to easy monitoring; (3) the output of the bureau is unmeasurable; (4) there are weak internal incentives to control efficiency; (5) information heterogeneity is possible; and (6) risk-aversion affects the performance of the bureaucrats.

The degree of monopoly power that the bureau possesses is positively related to the degree of cost inefficiencies expected within the bureau. The efficiency of a bureau is affected by potential competition for the supply of the same or a similar service.

As the size of the bureau increases, either by a larger number of employees or a larger jurisdiction, it becomes harder from the outside to observe inefficiencies. This problem is similar to the citizen - politician problem, but here potential for more waste exists. That is because the politician is in a competitive political market where he is more likely to be careful in obvious misconduct, but the bureaucrat is usually in a long-term, secure job and is less visible.

The output of the bureaus is usually some public good that is unmeasurable and/or indivisible. Moreover, the relation between the input per unit cost and the output is usually blurry and hard to quantify. Quality of service offered by a bureau to the users of the product cannot be quantified and rewarded since there is no pricing mechanism as in the private market that signals the existence of higher quality to the politicians in charge of appropriating the bureau's budget.

Weak internal incentives lead to inefficiency behavior. In the case of bureaus, internal incentives for minimizing wasteful behavior is weak: most public bureaucrats' salaries are either unrelated or indirectly , and perhaps inversely (Warren, Jr., 1975), related to improved efficiency.

The bureau is usually in a better bargaining position if the bureau knows the sponsor's demand while the sponsor is ignorant of the bureau's cost. This information asymmetry is intensified when the bureau's staff possess some technical expertise and the sponsor has to blindly rely on the technical reports of the bureau's staff such as is in the case of special districts.

This literature predicts that agencies that are run by bureaucrats in my case study choose less cost efficiently than other types of agencies. Thus, independent special districts that are led by appointed and not elected officials are more likely to have a smaller negative coefficient for vehicle cost variable than would independent agencies or general governments headed by elected officials.

7.2.4 What Role Does Risk-Aversion Have In Politicians' And Bureaucrats' Decision-Making?

If we assume risk-aversion as a characteristic of the politicians and bureaucrats, then we expect that they avoid engaging in activities that could be harmful to their career or their job. Thus, if there is a great enough chance that a bureaucrat or a politician may get caught behaving wastefully, he or she would avoid such behavior more so than would a risk-neutral person. It is plausible to think of a bureaucrat to be generally more risk averse than an average citizen. Hence, assuming risk-aversion, we expect that those agencies that could be monitored more directly by the citizens or sponsors/funding agencies are less likely to perform inefficiently. Risk-aversion, thus, may move a budget maximizing bureau back toward the efficient [budget] bureau size. But risk aversion can induce bureaus to avoid projects that their sponsors would want them to undertake, if the sponsors could costlessly monitor all bureau activities. Gist & Hill (1981) reported that officials of the Department of Housing and Urban Development allocated funds to cities with less risky investment projects to avoid the criticism if the projects were not successful. Yet, the purported goal of the program was to help "distressed" cities, that is, cities for which the risks in housing programs were high. (Mueller, 1989, Chapter 14) At the same time, the more visible the agency is, the more likely it is for it to divert funds to projects or expenditures that are more acceptable to the voters and avoid spending money on items that are questionable, such as Alternative Fuel Vehicles for their fleets. Alternative fuel vehicles are gentler to the environment and may be socially optimum choices, but they are not cost efficient to an specific establishment. This is mainly because vehicle consumers are not charged for the environmental damages due to their vehicles' operation. Given the above explanation, agencies run directly by politicians, I expect, are less likely to choose Alternative Fuel Vehicles in this case study.

7.2.5 How Does Government's Monopoly Power Lead to Cost Inefficiency?

If it was possible for citizens to choose among multiple cities or counties to get the same or similar public services, the outcome would have been more efficient local governments. The presence of competition, Mueller (1989) argues, tends to have the same salutary effect on efficiency that competition among firms does. Niskanen (1994) explains that competition - even if only latent - reduces the cost of monitoring a bureau, increases the credibility of a threat to transfer funding away from one bureau, and increases the incentive for each bureau to compete on an efficiency basis.

With this in mind, I expect to see city and county governments show more cost concerns than independent special districts run by appointed officials when choosing vehicles from the given list. Reasons for this are as follows: (1) City and county offices are headed by elected official operating in a competitive political market of vote-seeker politicians, while special districts are headed by career bureaucrats with secure long-term jobs. (2) The city and county governments are confined to set jurisdictions that, for the most part, cannot be expanded. Special districts, on the other hand, are created mostly to overcome these jurisdictional boundaries and are usually assigned much wider geographic jurisdictions, (Burns, 1994) which creates an almost non-contestable monopoly power for the districts. City and county governments' functions could, however, be challenged by other cities or counties in the region offering the same services to their constituents.

I expect to find a more negative vehicle cost coefficient for city and county governments and a lesser negative coefficient for special districts run by appointed officials.

7.2.6 Choosing Between Long-term Social Benefits Or Salient Short-Term Projects?

Let's look closely at how different types of government agencies allocate their funds. Suppose that a public agency is confronted with choosing between (1) a project that has very little (or perhaps negative) present rewards but is social welfare maximizing in a relatively distant future, and (2) a project that has immediate rewards but may lack long-term vision. What type of agency would more likely choose the first project over the second? I assert that an agency directly run by an elected official would consistently choose type (2) projects over type (1) projects. The nature of being periodically (at least every four years) subject to election would change the perspective of the official to one of more myopic perspective compared to a career bureaucrat that is not as much worried about his job. If we overcame all agency problems that I have listed earlier, one would expect that the appointed official would choose projects that may benefit the general population over longer time horizon. If senior bureaucrats have technical expertise their current job performance influences their reputation and long-term job prospects. Thus, in my case study, I expect to see special districts run by appointed officials choose alternative fuel vehicles more than city and county officials do, keeping all other attributes constant. Alternative fuel vehicles are thought to possess more environmental merits in the long-run, although not directly to the district, but less competitive short-term characteristics.

7.2.7 The Hypotheses That I Test

So far, I have argued reasons why I expect to see systematically differing decisions made regarding cost and environmental merits of products by various types of local governments. I organize and list these hypotheses in Table 20.

Table 20

Hypotheses Regarding Public Agencies' Behavior

Based on Models of Stated Choice of Alternative Fuel Vehicles (AFV)

Relative to the Gasoline Vehicles

Category	Prediction: AFV Coefficient's	Prediction: Emissions Levels Coefficient's	Prediction: Cost Coefficients'
Case 1: General government (city or county offices)	More negative than Case 2	Less negative than Case 2 (Possibly Positive Sign)	More negative than Case 2
Case 2: Independent special districts with appointed officials	Less negative than Case 1 (Possibly Positive Sign)	More negative than Case 1	Less negative than Case 1

7.3 THE EVIDENCE

7.3.1 The Data

I use four sources of data. The main source is the Alternative Fuel Vehicle Projects' fleet data that is described here in detail in Chapter 2. ~~I classify the observations for public agencies in one of the following four categories: 1) the elected environmentally sensitive, 2) the elected cost conscious, 3) the appointed environmentally sensitive, and 4) the appointed cost conscious. This task requires examining the data in two ways.~~ I classified the data into (1) public organizations, (2) public schools, and (3) private firms. My main analysis here is done using the first and second categories than represent public agencies in general. The survey data contained the agency name, the name and title of the person that filled out the survey, the address of the location of agency including the zipcode, as well as the data on its fleet. For studying different organizational affect of public agencies, I needed information on the specific type of government organization that each respondent belonged to. Thus, I supplemented the data on the public agencies and public schools with these new sources of data: (1) the 1992 Census of Government's publication on *Government Organization*, (2) California State Controller's Office's publication on *State and Local Government Finance*, and (3) phone interviews with the agencies administrative officers.

I combined the information from the fleet survey and supplemental data sets and coded public agencies into several functional categories: (1) general government (city and county offices), (2) independent special districts run by elected officials, (3) independent special districts run by appointed officials, and (4) public schools. The frequency distribution of these categories is shown in Tables 21 and 22, and Figure 3.

Table 21

Breakdown of Private and Public Organizations

Organization Type	***Frequency***	***Percentage Of Total Records***
All organizations	14523	100%
Private organizations	10542	72.59%
Public organizations	3981	27.41%
General Governments	1809	12.46%
School Districts	1347	9.25%
Special Districts	633	4.3%
Special districts run by elected officials	327	2.1%
Special districts run by appointed officials	306	2.0%

One concern with this type of survey data could be that the responses may vary depending on the authority and knowledge of the person filling out the questionnaire. In other words, there might be systematic differences in the stated choices if one respondent has a higher managerial position than another one. To examine the possibility of such bias, I decided to run my models controlling for the respondent's title. Thus, I coded the responses into two groups of *high level officials* and low *level officials* based on the respondents' job titles.[17]

[17] I thank Professor Gordon (Pete) Fielding for his assistance in classifying respondents' title.

7.3.2 General Governments Versus Special Districts

Local public organizations could be categorized into two distinct groups: (1) general governments consisting of city and county governments, and (2) special districts. Within special districts, there are those which are functionally and financially independent from any city or county government, and there are dependent special districts. Although, technically, according to the Census of Government's definition, only independent special districts are "special districts", in the state level, both independent and dependent districts are included in financial reports prepared by California State's Controller Office. I define a "special district" as one that is financially and operationally independent of city and county governments. In my analysis, henceforth, I do not include "dependent special districts" with special district category, but I add those to the "general government category".

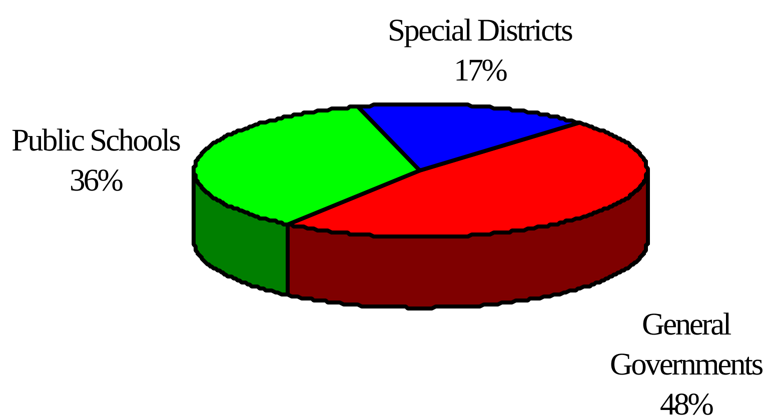
In my sample, special districts constituted about one-third of the observations as general governments. One-half of these special districts was led by elected officials, and one-half was run by appointed officials. The descriptive statistics for these categories are listed in Table 22.

Table 22

Breakdown of Various Types of Public Organizations

Public Organization Type	*Frequencies*	*Percentage of Total Records*
General Governments - Elected Officials	1809	47%
School Districts - Elected Officials	1347	36%
Special Districts	633	17%
Special districts run by elected officials	327	9%
Special districts run by appointed officials	306	8%

Figure 3
Various Types of Public Organizations



7.3.3 Methodology

I assumed that the fleet manager perfectly reflects the choices of the director(s) of the office in his stated choice answers and followed the multinomial Conditional Logit models as I have described earlier in Section 4.1.

7.3.4 Empirical Results

I built a simple multinomial logit model of public organizations' fuel choice explained by: (a) fuel constants where gasoline fuel constant is chosen as the base, (b) purchasing cost of the vehicle, (c) purchasing cost of the vehicle for large fleets only, (d) purchasing cost squared, (e) operating cost of the vehicle, (f) operating cost squared, (g) vehicle range, (h) vehicle range squared, (i) emission levels compared to 1993 gasoline vehicle, and (j) emission levels squared. I added some squared terms for continuous variables purchasing cost, operating cost, vehicle range, and emission levels, to account for possible non-linearity.

First, I tested the effect of the respondent's management level on the stated fuel choices. I set up a model of fuel choice for public agencies which had data on the respondent's management ranking. I included interactions with a dummy variable that is equal to one for those agencies which had a low ranking manager as the respondent of our survey. The results are reported in Table 23. Consequently, I performed a Log-likelihood Test with a constrained model consisting of all variables in Table 23, except all interactions with "Low ranking management" dummy. The chi-squared value with 10 degrees of freedom for this test was 14.79. Thus, I could not reject the null hypothesis that the constrained model is a better model, at a 0.5 level of significance.[18] I , thus, proceeded assuming that no systematic response variations between the two categories of high and low management respondents.

[18] Note that $c^{2}_{10,\ 0.5} = 18.31$.

Table 23

Testing the Effect of Management Level of the Respondents

Dependent Variable is Vehicle Fuel Choice Fuel Choice Base is Gasoline	Coefficient	Standard Error	t-statistic
EV constant	-0.006	0.52	-0.011
CNG constant	-0.336	0.36	-0.942
Methanol constant	-0.936	0.33	-2.846
Purchasing cost	-0.147	0.56	-0.261
Purchasing cost for fleets over 120 vehicles	-1.23	3.8	-0.321
Purchasing cost squared	-0.024	0.05	-0.466
Vehicle range	-0.532	0.34	-1.552
Vehicle range squared	0.174	0.12	1.432
Tailpipe Emission Level	3.924	1.77	2.211
Tailpipe Emission Level squared	-3.452	1.54	-2.239
EV constant * Low ranking management	-0.928	0.62	-1.487
CNG constant * Low ranking management	0.177	0.43	0.416
Methanol constant * Low ranking management	0.439	0.39	1.111
Purchasing Cost * Low ranking management	-0.455	0.65	-0.697
Purchasing cost for fleets over 120 vehicles * Low ranking management	-0.641	4.63	-0.139
Purchasing cost squared * Low ranking management	0.066	0.06	1.15
Range * Low ranking management	0.832	0.41	2.028
Range squared * Low ranking management	-0.240	0.14	-1.661
Tailpipe Emission Level * Low ranking management	-4.952	2.09	-2.373
Tailpipe Emission Level squared * Low ranking management	4.352	1.83	2.378

Initial Log-likelihood = -933.85 Pseudo R^2 = 0.055
Final Log-likelihood = -882.42 Number of Observations = 2234
Notes:
(1) I did not have data on the title of the respondents for about 16% of public agencies. (2) I did not include public schools here.

I then proceeded with estimating six fuel choice models for (1) private firms, (2) all public agencies, (3) general governments, (4) independent special districts, (5) independent special districts run by appointed officials, and (6) public agencies run by elected officials. I found that private agencies and public agencies systematically make different choices on their vehicle fleet. Table 24, models 1 and 2 show these findings. The cost coefficient for *public* organizations (model 2) is significant and less in absolute magnitude than it is for all *private firms* (model 1).

I compared the purchasing cost coefficient estimates across these six models and found that *special districts governed by appointed officials*, model 6, has a positive cost coefficient estimate, indicating a lesser level of cost concern in that segment. Moreover, *general government* segment had a significant and negative coefficient which was even higher in absolute value than *private firms'* segment, which indicates more cost concerns on the part of the general government officials. Note that the coefficient estimate for "purchasing cost squared" is positive and significant for both *general governments* and *agencies run by elected officials*, which indicate more sensitivity towards "purchasing cost" as the dollar amount of vehicle becomes larger. These findings are consistent with the hypothesis that *general governments* and other *public agencies run by elected officials* are more likely to make purchasing decisions that value lower prices than are *special districts run by appointed officials*.

Table 24

Conditional Multinomial Logit Models of Fuel Choice

Choice base is gasoline

** Coefficient is significant at 95% level.
* Coefficient is significant at 90% level.

	private firms model (1)	Std. Error	**public org. model (2)**	Std. Error	**general gov. model (3)**	Std. Error
EV constant	-1.030**	0.136	-0.721**	0.216	-0.418	0.324
CNG constant	-0.608**	0.089	-0.376**	0.144	-0.067	0.214
Methanol constant	-0.592**	0.081	-0.792**	0.136	-0.857**	0.203
Purchasing cost	-0.754**	0.136	-0.448**	0.198	-0.959**	0.321
Purchasing cost for fleets over 120 vehicles	0.130	0.172	-0.209	0.149	-0.207	0.190
Purchasing cost squared	0.047**	0.011	0.027*	0.014	0.071**	0.024
Vehicle range	0.394**	0.096	0.007	0.136	-0.085	0.204
Vehicle range squared	-0.061*	0.032	-0.001	0.048	0.032	0.072
Tailpipe emission	0.499	0.417	0.324	0.671	1.715*	1.018
Tailpipe emission squared	-0.385	0.376	-0.336	0.597	-1.563*	0.908
Pseudo-R2		0.1229		0.0448		0.0596
No. of observations		10542		3981		1809
Initial log-likelihood		-4208.82		-1639.04		-759.32
Final log-likelihood		-3691.68		-1565.56		-714.01

Table 25

Conditional Multinomial Logit Models of Fuel Choice

Choice base is gasoline

** Coefficient is significant at 95% level.
* Coefficient is significant at 90% level.

	Special Districts Model (4)	Std. Error	**Special districts with Appointed Officials Model (5)**	Std. Error	**Agencies with Elected Officials Model (6)**	Std. Error
EV constant	-1.078**	0.535	-1.840**	0.764	-0.678**	0.232
CNG constant	-0.861**	0.373	-1.327**	0.534	-0.328**	0.155
Methanol constant	-0.360	0.323	-0.660	0.469	-0.818**	0.145
Purchasing cost	0.627	0.597	1.260	0.811	-0.494**	0.213
Purchasing cost for fleets over 120 vehicles	-0.396	0.482	-0.838	0.670	-0.174	0.153
Purchasing cost squared	-0.070	0.055	-0.095	0.068	0.030**	0.015
Vehicle range	0.166	0.375	-0.106	0.537	-0.042	0.146
Vehicle range squared	-0.039	0.125	-0.109	0.184	0.028	0.052
Tailpipe emission	-0.195	1.829	-1.889	2.746	0.362	0.713
Tailpipe emission squared	0.227	1.604	2.222	2.452	-0.432	0.634
Pseudo-R^2		0.0731		0.0736		0.0508
No. of observations		632		305		3483
Initial log-likelihood		-256.31		-121.62		-1438.78

Final log-likelihood	-237.57	-112.67	-1365.69

7.3.5 Alternative Fuel Vehicle Choice, Emission Levels, and Public Organizations

The results from Tables 24 and 25 also indicate some interesting findings regarding alternative fuel choices made by different types of public organizations. For example, *agencies run by elected officials* and *general governments* seemed to be more likely to choose Compressed Natural Gas (CNG) than *special districts run by appointed officials,* holding other attributes constant. Again, there is a systematic divergence of choice behavior between *special districts run by appointed officials* and all other forms of local government organizations which are run by elected officials. The same story is true for the electric vehicle choice. The story, however, changes for the methanol choice: *special districts run by appointed officials* are more likely to purchase methanol vehicles than any other public organization group. But, what does this result say about long-term social welfare concerns versus short-term goals? A look at the coefficient estimates for "tailpipe emission" variable may shed some light on this issue. Compare *general governments'* "tailpipe emission" coefficient with that of *special districts run by appointed officials*. For *general governments,* the "tailpipe emission" coefficient is positive while for *special districts run by appointed officials,* this coefficient is negative. This result indicates less sensitivity on the part of *general governments* than *special districts run by appointed officials* toward emission levels when making vehicle choices. The "tailpipe emission" coefficient estimate for *public agencies run by elected officials* is positive but smaller than that of *general governments.* This is consistent with local governments' encompassing smaller geographic areas and thus not caring as much about air pollution which affects areas outside of their jurisdiction.

The above results are consistent with the hypothesis that (1) general governments, which are all run by elected officials, exhibit the least amount of concern for environmental merits of their chosen vehicles, and (2) special districts run by appointed officials show the most environmental sensitivity in their vehicle choices.

7.3.6 Fleet Size and Cost Efficiency

Earlier in this dissertation, I showed that larger public agencies seemed to behave more like private agencies with respect to cost concerns. (Please see Model D) The question remained that *what is it about larger public agencies that makes them choose more like private firms than small public agencies do?* So far, my analysis did not present any hypothesis as to why would that be the case. On the contrary, if anything, I showed so far that larger public agencies are generally more cost inefficient because larger size of an organization reduces the probability of adequate external monitoring and makes internal inefficiency less visible. Thus, we should expect to see less cost sensitivity from larger public agencies as opposed to what Model D predicts.

A closer look at the distribution of fleet size in the surveyed agencies reveals that in our fleet survey, public agencies are mostly larger fleets of over 120 vehicles. Figure 2 shows that public agencies constitute over 65% of “large fleets” in our sample. Within public agencies, as Figure 3 shows, most of the larger fleets belonged to city and county offices, i.e., general governments. Special districts had the least proportional fleets of larger size than all other categories. Thus, *larger public agency* category in Model D overwhelmingly consists of *general governments* and only a minute portion of special districts are represented in it. So the results from Model D, I hypothesize, may actually show the similarity of *general governments'* cost concerns to the private sector, as my analysis hypothesizes. Hence, I decided to test this hypothesis.

Figure 4: Comparison of Public and Private Agencies' Fleet Size Distribution

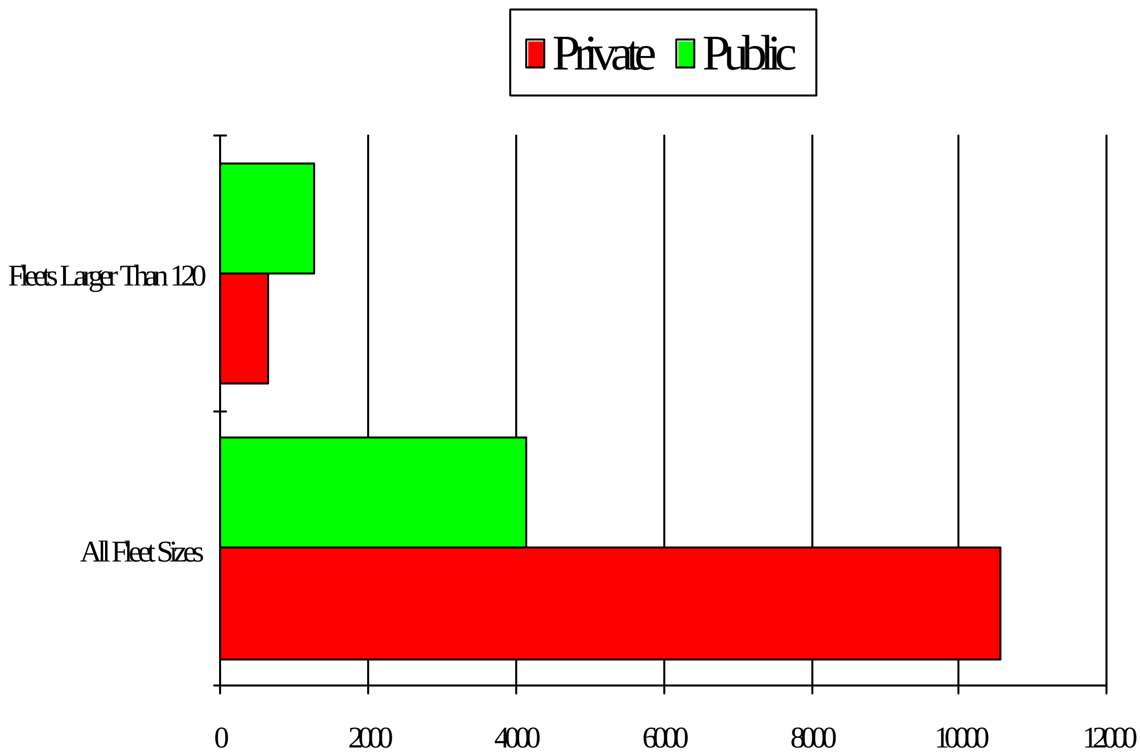
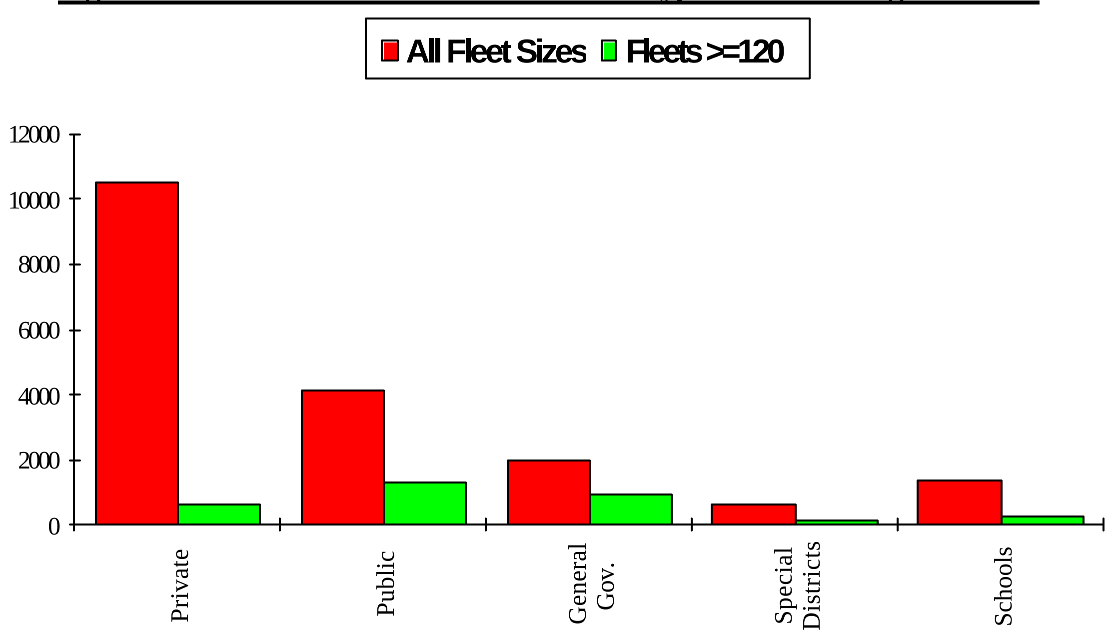


Figure 5: Fleet Size Distribution of Various Types of Public Organizations



I set up a model of fuel choice with interaction variables for (1) all public agencies, (2) large public agencies, and (3) large general government agencies. Results are shown in Table 26. I tested a series of hypotheses to investigate whether or not differences in cost concerns and fuel choices exist between the private, public, large public, and large general government organizations. Table 27 contains the complete set of tests and their results from model estimated in Table 26. I could not reject the hypothesis that "larger public fleets have the same cost coefficient than do larger general government fleets" at 95% confidence level using a Log-Likelihood Ratio Test .

In a similar model, shown in Table 28, I included interactions for all *general governments* regardless of their fleet sizes. Using this model, I tested further hypotheses comparing all general government organizations with all sampled organizations, all public organizations, and large public organizations. A subset of tests are shown in Table 29. These tests also show further evidence that general government organizations do appear to choose more cost-consciously than do other public organizations, and that general governments do seem to value lower purchasing cost of the vehicles as much as private firms do. These findings are consistent with my prediction that general government offices, which are run by elected officials, are more concerned with vote-maximizing and appearing to be cost-efficient.

Table 26

Conditional Multinomial Logit Model
Large and Small Public Agencies & Large General Government Fleets Are Tested Against All Industries

Number of obs = 14523 Initial Log Likelihood =-5850.8782
Pseudo R2 = 0.1060 Final Log Likelihood = -5230.5913

Fuel Choice (Base is gasoline vehicles)	**Coef.**	**SE**	**t-stat**
EV constant	-1.384	0.107	-12.910
CNG constant	-0.632	0.074	-8.503
Methanol constant	-0.455	0.057	-7.950
Purchasing cost	-0.675	0.110	-6.157
Purchasing cost for fleets over 120 vehicles	0.148	0.173	0.855
Purchasing cost squared	0.039	0.009	4.377
Operating Cost	-0.047	0.009	-4.918
Vehicle range	0.219	0.033	6.621
EV constant * general governments with over 120 vehicles	-0.745	0.588	-1.268
CNG constant * general governments with over 120 vehicles	0.558	0.558	1.000
Methanol constant * general governments with over 120 vehicles	-0.640	0.436	-1.469
Purchasing cost * general governments with over 120 vehicles	-0.054	0.282	-0.192
Vehicle range * general governments with over 120 vehicles	-0.153	0.232	-0.657
EV constant * all public organizations	0.379	0.185	2.046
CNG constant * all public organizations	0.149	0.159	0.936
Methanol constant * all public organizations	-0.258	0.130	-1.979
Purchasing cost * all public organizations	0.059	0.083	0.709
Vehicle range * all public organizations	-0.203	0.070	-2.916
EV constant * all public organizations with over 120 vehicles	0.377	0.503	0.749
CNG constant * all public organizations with over 120 vehicles	-0.136	0.497	-0.274
Methanol constant * all public organizations with over 120 vehicles	0.400	0.375	1.068
Purchasing cost * all public organizations with over 120 vehicles	-0.298	0.292	-1.021
Vehicle range * all public organizations with over 120	0.052	0.204	0.256

vehicles			

<u>**Table 27**</u>

Log-Likelihood Ratio Tests
Performed on constraint models as described below with the model described in Table 26 being the saturated model

Null Hypothesis	Chi^2 (1)	Prob> Chi^2	Conclusion
β (EV constant for all organizations) = β (EV constant for all public organizations)	50.44	0.000	reject H_o
β (CNG constant for all organizations) = β (CNG constant for all public organizations)	14.68	0.0001	reject H_o
β (methanol constant for all organizations) = β (methanol constant for all public organizations)	1.45	0.2283	cannot reject H_o
β (purchasing cost for all organizations) = β (purchasing cost for all public organizations)	29.06	0.0000	reject H_o
β (vehicle range for all organizations) = β (vehicle range for all public organizations)	21.91	0.000	reject H_o
β (EV constant for all organizations) = β (EV constant for all public organizations with large fleets)	11.75	0.0006	reject H_o
β (CNG constant for all organizations) = β (CNG constant for all public organizations with large fleets)	0.97	0.3243	cannot reject H_o
β (methanol constant for all organizations) = β (methanol constant for all public organizations with large fleets)	5.09	0.0241	reject H_o
β (purchasing cost for all organizations) = β (purchasing cost for all public organizations with large fleets)	1.45	0.2283	cannot reject H_o
β (vehicle range for all organizations) = β (vehicle range for all public organizations with large fleets)	0.65	0.4198	cannot reject H_o
β (EV constant for all organizations) = β (EV constant for general government organizations with large fleets)	1.14	0.2856	cannot reject H_o
β (CNG constant for all organizations) = β (CNG constant for general government organizations with large fleets)	4.46	0.0347	reject H_o
β (methanol constant for all organizations) = β (methanol constant for general government	0.18	0.6739	cannot reject H_o

Null Hypothesis	Chi^2 (1)	Prob> Chi^2	Conclusion
organizations with large fleets)			

Table 27 (continued)

Log-Likelihood Ratio Tests
Performed on constraint models as described below with the model described in Table 26 being the saturated model

Null Hypothesis	Chi^2 (1)	Prob> Chi^2	Conclusion
β (purchasing cost for all organizations) = β (purchasing cost for general government organizations with large fleets)	4.15	0.0417	reject H_o
β (vehicle range for all organizations) = β (vehicle range for general government organizations with large fleets)	2.52	0.1127	cannot reject H_o
β (EV constant for all public organizations with large fleets) = β (EV constant for all public organizations)	0.00	0.997	cannot reject H_o
β (CNG constant for all public organizations with large fleets) = β (CNG constant for all public organizations)	0.26	0.6103	cannot reject H_o
β (methanol constant for all public organizations with large fleets) = β (methanol constant for all public organizations)	2.34	0.1259	cannot reject H_o
β (purchasing cost for all public organizations with large fleets) = β (purchasing cost for all public organizations)	1.2	0.2726	cannot reject H_o
β (vehicle range for all public organizations with large fleets) = β (vehicle range for all public organizations)	1.21	0.272	cannot reject H_o
β (EV constant for all public organizations with large fleets) = β (EV constant for general government organizations with large fleets)	1.2	0.274	cannot reject H_o
β (CNG constant for all public organizations with large fleets) = β (CNG constant for general government organizations with large fleets)	0.48	0.4906	cannot reject H_o
β (methanol constant for all public organizations with large fleets) = β (methanol constant for general government organizations with large fleets)	1.85	0.1734	cannot reject H_o

<u>Table 27 (continued)</u>

Log-Likelihood Ratio Tests
Performed on constraint models as described below with the model described in Table 26 being the saturated model

Null Hypothesis	Chi^2 (1)	Prob> Chi^2	Conclusion
β (purchasing cost for all public organizations with large fleets) = β (purchasing cost for general government organizations with large fleets)	0.22	0.6354	cannot reject H_o
β (vehicle range for all public organizations with large fleets) = β (vehicle range for general government organizations with large fleets)	0.24	0.6209	cannot reject H_o

Table 28

Conditional Multinomial Logit Model
Large and Small Public Agencies & all General Government Fleets
Are Tested Against All Industries

Initial Log Likelihood = -5850.88 Number of obs = 14523
Final Log Likelihood = -5235.27 Pseudo R2 = 0.1052

Fuel Choice (Base is gasoline vehicles)	**Coef.**	**SE**	**t-stat**
EV constant	-1.382	0.107	-12.895
CNG constant	-0.631	0.074	-8.498
Methanol constant	-0.455	0.057	-7.954
Purchasing cost	-0.676	0.110	-6.149
Purchasing cost for fleets over 120 vehicles	0.000	0.000	0.854
Purchasing cost squared	0.039	0.009	4.373
Operating Cost	-0.046	0.009	-4.889
Vehicle range	0.219	0.033	6.622
EV constant * general governments with over 120 vehicles	-0.085	0.302	-0.280
CNG constant * general governments with over 120 vehicles	0.322	0.263	1.227
Methanol constant * general governments with over 120 vehicles	-0.051	0.220	-0.233
Purchasing cost * general governments with over 120 vehicles	0.058	0.136	0.430
Vehicle range * general governments with over 120 vehicles	-0.012	0.114	-0.110
EV constant * all public organizations	0.401	0.207	1.939
CNG constant * all public organizations	0.038	0.182	0.211
Methanol constant * all public organizations	-0.243	0.147	-1.648
Purchasing cost * all public organizations	0.042	0.090	0.473
Vehicle range * all public organizations	-0.204	0.079	-2.592
EV constant * all public organizations with over 120 vehicles	-0.041	0.336	-0.122
CNG constant * all public organizations with over 120 vehicles	0.197	0.299	0.658
Methanol constant * all public organizations with over 120 vehicles	0.002	0.249	0.006
Purchasing cost * all public organizations with over 120 vehicles	-0.359	0.239	-1.504
Vehicle range * all public organizations with over	-0.024	0.128	-0.191

120 vehicles			

<u>Table 29</u>

Log-likelihood Ratio Tests
Performed on constraint models as described below with the model described in Table 28 being the saturated model

Null Hypothesis	Test Results
β (purchasing cost for all respondents) = β (purchasing cost for public agencies only)	Reject H_o
β (vehicle range for all respondents) = β (vehicle range for public agencies only)	Reject H_o
β (purchasing cost for all respondents) = β (purchasing cost for general government organizations only)	Reject H_o
β (vehicle range for all respondents) = β (vehicle range for general government organizations only)	Cannot reject H_o
β (purchasing cost for larger public organization fleets) = β (purchasing cost for general government organizations only)	Cannot reject H_o

SUMMARY AND CONCLUSION

In this paper, I examined how choices made by public organizations differ from those of private organizations when complex purchase decisions are involved which are conflicting in environmental and cost issues. I investigated the underlying motives for these differences and how the specific structure of the public institution affects its decision-making process. Institutional features, such as the relationship of the organization to the city or the county governments and whether or not the organization is a bureaucracy or an independent district, were examined. I also explored how public choice issues such as having an elected or an appointed governing body affected public organizations' choices. I used the Alternative Fuel Vehicle Fleet survey as well as other sources of data and empirically tested various hypotheses regarding the behavior of different types of public agencies in the context of a stated choice experiment on vehicle purchases.

One hypothesis that I tested, for example, was that the incentives and agency goals of elected officials and appointed officials differ fundamentally. Elected officials are concerned with getting votes in the next election. They would like to project the image that they have allocated and used their budgets efficiently and have made purchasing decisions that were cost-minimizing. Appointed bureaucrats usually have more secure jobs and usually specialize in the task their particular office performs. Whereas the top public bureaucrats may (and generally do) serve at the pleasure of elected officials, their connection to electoral incentives is likely to be attenuated. Their purchasing choices may reflect more long-term horizons and social welfare gains. However, they do not have much incentive to choose cost-efficiently since their incomes (and their jobs) are relatively secure and not directly related to their organizations' cost efficiency. Thus I predicted that elected officials choices reflect more cost concerns while appointed officials choices show more environmentally friendly behavior.

My empirical results were consistent with hypothesis that there exists systematic choice differences between special districts run by appointed officials and local government agencies run by elected officials. These findings demonstrate that being subject to re-election would serve as an internal monitoring device for special districts and other government organizations, encouraging them to make more cost conscious decisions. The tradeoff is that environmentally welfare enhancing projects with longer-term implementations may get sacrificed!

Appendix I

Example 1: Task **From the Stated Preference Choice Allocation Survey Showing one of 64 Experimental Treatments**

Assume that you must now replace your entire fleet of CARS AND STATION WAGONS by using the three types of CARS AND STATION WAGONS described in the table below.

CARS AND STATION WAGONS

Fuel Type	Gasoline	Electric	Natural Gas (CNG)
Dual Fuel Ability			Can also run on gasoline
Capital Cost Per Vehicle	$17,000	$14,000 (includes recharge unit)	$16,000
Vehicle Range	250 miles	100 miles	275 miles on CNG
Operating Costs	6 cents per mile	4 cents per mile of overnight recharging. 12 cents per mile for daytime recharging.	4 cents per mile
On-Site Refueling	On-site refueling not available	recharging unit comes with each vehicle for on-site use.	Not Applicable
Refueling Time	Not Applicable	3 Hr. for full charge	Not Applicable
Service Station Refueling	Gasoline available at current stations	5 recharge stations for every 10 gasoline stations	1 CNG station for every 10 gasoline stations
Refueling Time	7 min. to fill empty tank	60 min. for full charge	5 min. to fill empty CNG tank
Home Refueling	Not Available.	Can recharge at home overnight.	CNG home refueling units cost $4,000
Refueling Time			6 Hrs. to full empty CNG tank
Tailpipe emissions	25% of new 1993 gasoline car emissions	Zero tailpipe emissions	40% of new gasoline car emissions

How would you replace your entire fleet of CARS AND STATION WAGONS from the three vehicle choices described in the proceeding table? Under each fuel type indicate the number of vehicles you would require for each use.

Replacement of CARS AND STATION WAGONS

VEHILCE USAGE	Gasoline	Electric	Natural Gas (CNG)
SALES OR CUSTOMER VISITS	________________	________________	________________
SHUTTLE / RIDESHARING / COMMUTE	________________	________________	________________
Other uses: ______________	________________	________________	________________
Total:	________________	________________	________________

If you ruled out any vehicle type in the above table, please describe why:
____

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Example 1: From the Stated Preference Choice Allocation Survey Task Showing one of 64 Experimental Treatments

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Vehicle Range	250 miles	100 miles	275 miles on CNG
Operating Costs	6 cents per mile	4 cents per mile of overnight recharging. 12 cents per mile for daytime recharging.	4 cents per mile
On-Site Refueling	On-site refueling not available	recharging unit comes with each vehicle for on-site use.	Not Applicable
Refueling Time	Not Applicable	3 Hr. for full charge	Not Applicable
Service Station Refueling	Gasoline available at current stations	5 recharge stations for every 10 gasoline stations	1 CNG station for every 10 gasoline stations
Refueling Time	7 min. to fill empty tank	60 min. for full charge	5 min. to fill empty CNG tank
Home Refueling	Not Available.	Can recharge at home overnight.	CNG home refueling units cost $4,000
Refueling Time			6 Hrs. to full empty CNG tank
Tailpipe emissions	25% of new 1993 gasoline car emissions	Zero tailpipe emissions	40% of new gasoline car emissions

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Replacement of CARS AND STATION WAGONS

VEHILCE USAGE	Gasoline	Electric	Natural Gas (CNG)
SALES OR CUSTOMER VISITS	________________	________________	________________
SHUTTLE / RIDESHARING / COMMUTE	________________	________________	________________
Other uses: _______________	________________	________________	________________
Total:	________________	________________	________________

If you ruled out any vehicle type in the above table, please describe why: ___________________________________

Appendix II

Assumed Price and Operating Characteristics For Year 2010

Gasoline Vehicles	Price	Refueling Time	Emission Index	Range	Luggage Index	Operating Cost (¢/mi)	Station Availability
Minicar	14227	7	0.52	400	1	4.15	1
Subcompact car	13452	7	0.52	400	1	4.55	1
Compact car	18178	7	0.52	400	1	5.42	1
Intermediate car	20320	7	0.52	400	1	5.98	1
Large car	22075	7	0.52	400	1	6.42	1
Luxury car	38749	7	0.52	400	1	7.41	1
Sports car	18725	7	0.52	400	1	6.26	1
Compact pickup	14770	7	0.52	400	0	6.54	1
Standard pickup	18578	7	0.86	400	0	9.09	1
Minivan	21278	7	0.86	400	0	7.06	1
Standard var	19036	7	0.86	400	0	8.99	1
Trucks	60,000	7	2.5	400	0	20	1
Small Buses	60,000	7	2.5	400	0	20	1

Appendix II

Assumed Price and Operating Characteristics For Year 2010

Methanol Vehicles	Price	Refueling Time	Emission Index	Range	Luggage Index	Operating Cost (¢/mi)	Station Availability
Minicar	14527	7	0.52	280	1	5.75	0.3
Subcompact car	13752	7	0.52	280	1	6.15	0.3
Compact car	18478	7	0.52	280	1	7.02	0.3
Intermediate car	20620	7	0.52	280	1	7.58	0.3
Large car	22375	7	0.52	280	1	8.02	0.3
Luxury car	39049	7	0.52	260	1	9.01	0.3
Sports car	19025	7	0.52	280	1	7.86	0.3
Compact pickup	15070	7	0.86	300	0	8.14	0.3
Standard pickup	18878	7	0.86	300	0	10.69	0.3
Minivan	21578	7	0.86	300	0	8.66	0.3
Standard var	19336	7	0.86	300	0	10.59	0.3
Trucks (<=14K Ibs)	60300	7	0.86	300	0	21.6	0.3
Small Buses	60300	7	0.86	300	0	21.6	0.3

Appendix II

Assumed Price and Operating Characteristics For Year 2010

CNG Vehicles	Price	Refueling Time	Emission Index	Range	Luggage Index	Operating Cost (¢/mi)	Station Availability
Minicar	16627	5	0.09	180	1	3.25	0.2
Subcompact car	15852	5	0.09	180	1	3.65	0.2
Compact car	20578	5	0.09	180	1	4.52	0.2
Intermediate car	22720	5	0.09	180	1	5.08	0.2
Large car	24475	5	0.31	180	1	5.52	0.2
Luxury car	41149	5	0.31	180	1	6.51	0.2
Sports car	21125	5	0.31	180	1	5.36	0.2
Compact pickup	17170	5	0.31	180	0	5.64	0.2
Standard pickup	20978	5	0.31	180	0	8.19	0.2
Minivan	23678	5	0.31	180	0	6.16	0.2
Standard var	21436	5	0.31	180	0	8.09	0.2
Trucks (<=14K Ibs)	62400	5	0.31	180	0	19.1	0.2
Small Buses	62400	5	0.31	180	0	19.1	0.2

Appendix II

Assumed Price and Operating Characteristics For Year 2010

EV Vehicles	Price	Refueling Time	Emission Index	Range	Luggage Index	Operating Cost (¢/mi)	Station Availability	On-site refueling time - HRS .
Minicar	28627	10	0	150	1	7.75	0.1	4
Subcompact car	27852	10	0	150	1	8.15	0.1	4
Compact car	32578	10	0	150	1	9.02	0.1	4
Intermediate car	34720	10	0	150	1	9.58	0.1	4
Large car	36475	10	0	150	1	10.02	0.1	4
Luxury car	53149	10	0	150	1	11.01	0.1	4
Sports car	33125	10	0	150	1	9.86	0.1	4
Compact pickup	29170	10	0	150	0	10.14	0.1	4
Standard pickup	32978	10	0	150	0	12.69	0.1	4
Minivan	35678	10	0	150	0	10.66	0.1	4
Standard var	33436	10	0	150	0	12.59	0.1	4
Trucks (<=14K Ibs)	74400	10	0	150	0	23.6	0.1	4
Small Buses	74400	10	0	150	0	23.6	0.1	4

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