Three Essays in Energy and Environmental Economics

by

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Abstract

Motor vehicle emissions constitute a major source of local air pollution in the United States. The U.S. government stipulated motor fuel content regulations and required that cleaner fuels be adopted, instead of conventional gasoline, in certain pollution non-attainment areas. To determine the environmental effects of these regulations, the emissions levels that would have been reduced in the regulated areas in the absence of the regulations need to be known. However, this counter-factual does not exist. The difference-in-difference strategy employed in the current study takes the reductions in the emissions of control counties as a surrogate for the counter-factual of the regulated areas. I find that the introduction of gasoline content regulations results in a dramatic reduction in the pollution from on-road vehicles but not from off-road engines and vehicles, during the period 1990 to 2002. Therefore, the less affected pollution from the off-road sources could nullify the environmental benefits by adopting clean fuels. This may be an additional explanation for why local air quality did not improve though cleaner fuels were prescribed to certain polluted areas.

An accelerated vehicle retirement program was also adopted by the U.S. government to address vehicle air pollution. The U.S. "Cash for Clunkers" (CARS) program offered incentive to participants who retired their current vehicles and purchased a new vehicle, provided that certain requirements on fuel economy improvements and vehicle categories were satisfied. I evaluate the pollution-reduction effects of this program. Based on the rich set of household and vehicle characteristics contained in the 2009 National Household Travel Survey (NHTS) data, an instrumental variable regression is used to predict the travel demand for

the CARS retried and replacement vehicles and then their associated pollution. This study finds that the CARS program potentially does not result in a reduction of CO2 emissions and an environmental gain, even with taking into account its effects on the emissions of criteria pollutants.

The U.S. Corporate Average Fuel Economy (CAFE) standards have imposed increasingly stringent requirements on vehicle fuel economy. The improvement of fuel efficiency is motivated by the desire to reduce fuel consumption and vehicle carbon emissions. However, the improved fuel efficiency leads to a reduced per-mile cost of driving and thus additional travel demand, which is a direct rebound or “take back” effect, because it may offset the potential fuel savings that otherwise would be obtained. This study empirically identifies the rebound effect by estimating a joint model, which determinines vehicle miles and fuel efficiency simultaneously. The current study finds no evidence of the rebound effect and concludes that the potential negative effect resulting from the fuel efficiency improvement should not be a concern.

Preface

(Mandatory due to collaborative work)

I was responsible for the data collection and empirical analysis, as well as the manuscript composition of Chapter 1. Professor J. Marchand assisted with the model specification, presentation of the evidence, and manuscript editing. Dr. U. Chakravorty and Dr. J. Marchand were the supervisory authors of chapter 1. Chatper 2 and 3 of this thesis is my original work. Dr. U. Chakravorty and Dr. J. Marchand provided me with advisory suggestions for all three chapters. No part of this thesis has been previously published.

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I would like to express my sincere gratitude to my co-major professors, Dr. Ujjayant Chakravorty and Dr. Joseph Marchand, for their guidance, patience and support in every possible way. I am also indebted to the rest of my committee members, Dr. Heather Eckert, Dr. David Brown, Dr. Runjuan Liu, for their helpful comments and suggestions to this thesis. I would also thank Sumeet Gulati for his valuable comments.

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1.1 Introduction

Motor vehicle emissions constitute a major source of air pollution. This is an increasing problem worldwide, as modern roads encourage more drivers to drive more miles. Volatile organic compounds (VOCs), nitrogen oxides (NOx), carbon monoxide (CO), and particulate matter (PM) generated by motor vehicles are four distinct air pollutants which significantly affect both ambient air quality and human health.[1] To limit the pollution from vehicle usage, the U.S. federal government stipulated minimum motor fuel content requirements under the 1990 Clean Air Act Amendments (CAAA). Particularly, the government require that cleaner fuels instead of conventional gasoline be adopted in severely-polluted areas. For example, federal reformulated gasoline (RFG) and winter oxygenated gasoline (OXY) are used in ozone and CO non-attainment areas, respectively, as these two types of fuels are cleaner for these purposes.

[1] For more details on these pollutants, please see Section 2.

Beyond the federal regulations, states are also allowed to implement their own regional gasoline content regulations in certain pollution non-attainment areas under state implementation plans (SIPs) approved by the 1990 CAAA. A fuel under the SIPs is also cleaner than conventional fuel and is used to meet a state's own emission-reduction target and obtain the attainment designation for some certain pollutant(s). In addition, the state requirements are normally more stringent than the federal requirements. For example, state regulations may require a lower volatility limit on gasoline, a higher oxygen content in the fuel, or a longer policy control period compared to the federal regulations. The SIPs fuels are labeled "boutique fuels", while the Reid Vapor Pressure (RVP) gasoline is a commonly adopted boutique fuel.

Currently, over 17 types of gasoline are being sold in the U.S. fuel market, as a result of different regional fuel content requirements Brown et al. (2008).[2] In general, the gasoline types can be distinguished based on the fuel attributes including fuel volatility (measured by Reid Vapor Pressure), oxygen-content volume and type, and the volume of other fuel contents such as sulfur. Compared with conventional fuel, some types of clean fuels may have lower fuel volatility to reduce VOC emissions, which react with NOx to form ground-level ozone smog in the presence of sunlight. Some types may have the requirements to contain minimum fuel oxygen content to reduce CO emissions, which are primarily produced from the incomplete combustion of carbon content in fuel due to a lack of oxygen content, especially during the winter season. Besides the requirements on fuel volatility and oxygen content, a clean fuel may also need to meet the emission-reduction targets for toxic air pollutants (TAP) and NOx, and meet the limits on benzene as well, in order to be certified as reformulated gasoline.

The effects of the fuel content regulations on wholesale gasoline prices and price volatility were explored in Brown et al. (2008), Chakravorty et al. (2008), and Muehlegger (2006).

[2]For more information, see EPAct Section 1541(c): Boutique fuels report to congress, 2006: `http://www.epa.gov/otaq/boutique/420r06901.pdf`.

These authors found that the price gap was around three cents per gallon between regulated and uncontrolled areas due to the higher cost of producing cleaner fuels. Furthermore, some of these authors argued that the geographic segmentation resulting from different local regulations can provide potential market power to gasoline suppliers within isolated markets and, therefore, partially contribute to the price gap.

However, the effects of the regulations on reducing air pollution have not been well addressed. Auffhammer and Kellogg (2011) first examined how gasoline content regulations affected air quality, as measured by ground-level ozone concentration levels. They found that gasoline content regulations, with the exception of the California Air Resources Board (CARB) reformulated gasoline program, did not significantly reduce these ozone concentration levels, and thus, did not effectively improve air quality. The current paper is most closely related to their study, because it also is attempting to identify the effects of regulations on the reduction in air pollution. However, the emission levels for VOCs, NOx, and CO "directly" emitted by motor vehicles instead serve as the measures used to evaluate the pollution reduction effects of the regulations.

Through the use of the different measures, the current study finds that content regulations effectively reduced on-road vehicle emissions, a conclusion which seemingly contradicts Auffhammer and Kellogg (2011).[3] However, this apparent contradiction could be reconciled by understanding the differences between the emissions of air pollutants and the ozone concentration levels. Ground-level ozone is not emitted by any source but rather is produced by a chemical reaction between VOCs and NOx in the presence of sunlight. As a result, a clean fuel regulation could effectively reduce vehicle emissions but not improve air quality because, in addition to the emissions associated with the vehicle usage, the exhaust yielded by industrial processes, chemical solvents, and natural sources also contains VOCs and NOx, which additionally facilitates the forming of ozone and affects air quality.

[3]According to the National Emission Inventory (NEI), "on-road" emissions are defined as those created by motorized vehicles of normal operation on public roadways, which includes the emissions of passenger cars, motorcycles, minivans, sport-utility vehicles, light-duty trucks, heavy-duty trucks, and buses.

More specifically, the current paper tries to identify the emission-reduction effects resulting from the implementations of the relevant regulations, for both on-road vehicles and off-road engines and vehicles.[4] To determine the environmental effects, the emissions levels that would have been reduced in the regulated areas need to be known had the regulations not been adopted. However, this counter-factual does not exist. The difference-in-difference (D-in-D) strategy employed in the current paper takes the reductions in the emissions of control counties as a surrogate for the counter-factual of the treatment areas.

Based on the fuel types, counties across the United States are allocated into an RFG-treated group, an RVP-treated group, an OXY-treated group, and a control group in which conventional gasoline is used. By comparing the changes in pollution levels for both treated and control groups, the effects of the regulations on reducing VOCs, NOx, and CO are then determined in 1990 and from 1996 to 2002. Due to a lack of data for the interval from 1991 to 1995, the current empirical strategy is carried out based on two categories of treated counties: those that adopted a clean fuel in 1996 and those that adopted a clean fuel later than 1996.

With respect to the counties that fall into the first category, the reductions in emissions levels for regulated and control areas are compared between 1990 and 1996. All gasoline-content regulations are found to have had a significant effect in reducing the targeted pollution emitted by on-road vehicles. In 1996, the RFG program reduced VOCs, NOx, and CO by 35.5%, 16.9%, and 34.1% on average, respectively, at the county-level. These reductions are collectively valued at $37.83 million USD in 2010 prices. The RVP program also lead to a reduction of VOCs emissions by 30.6%, and the OXY program reduced CO by 35.4% at the county-level in 1996. These particular reductions are valued at approximately $11.68 and $16.20 million, respectively.[5] In addition, emission densities and emissions per capita were

[4] The off-road sources as defined by the NEI include the following general equipment categories: agricultural, airport support, light commercial, construction and mining, industrial, lawn and garden, logging, pleasure craft, railroad, and recreational equipment.

[5] Following Antweiler and Gulati (2011), Hydrocarbon (HC), NOx, and CO were valued at approximately $3.5, $3.5, and $0.5 CAD per kilogram in 2010 prices, respectively. The average annual exchange rate

used as the alternative dependent variables to examine the regulation effects. It is found that the former but not the latter was well influenced by the fuel regulations.

The regulation effects were also examined over time for the counties that switched into or out of a program in a year other than 1996. For counties that adopted RVP gasoline in 1998, 1999, and 2000, the estimates on the policy effects are all found to be negative (but mostly insignificant) and have a tendency to increase in magnitude over time. Therefore, the RVP program might perform better as a long-run emission-control strategy. Furthermore, for counties that switched out of the OXY program, the pollution reduction effects quickly cease over time.

Regarding off-road pollution, none of the policies were found to yield substantial pollution reductions. This finding is explained by the fact that gasoline is primarily consumed by on-road vehicles but not by off-road engines and vehicles. Because the emissions from on-road and off-road sources jointly promote the production of ground ozone, the increasing and unaffected off-road pollution may also explain why a substantial air quality improvement cannot be observed for some of the regulated areas.

More importantly, this finding also provides us with policy recommendations: governments should impose some complementary regulations to control the off-road emissions, majorly produced from diesel combustion, in order to prevent the environmental gains collected by the clean fuel regulations from being crowded out by the uncontrolled off-road pollution. As expected, Low sulfur (500 parts per million) and Ultra Low Sulfur Diesel (ULSD, 15 parts per million) fuels are being adopted by off-road, locomotive, and marine sectors from 2007-2014, although the main purpose of using these cleaner fuels is to reduce non-highway sulfur emissions.

between the USD and CAD was 1.02993904 in 2010.

1.2 Background on externalities and gasoline regulation

The major externalities associated with automobile usage may include local air pollution, global air pollution, oil dependency, traffic congestion, and traffic accidents Parry et al. (2007). The local and global air pollution are distinguished according to the potential influence scope of the pollution. VOCs, NOx, CO, and particulate matter (PM) generated by motor vehicles are local pollutants and tend to affect local air quality, while carbon dioxide (CO2) is well known as a global pollutant and the major component of greenhouse gases, which impose a significant impact on global warming. In the current paper, only local pollutants are focused on, as the gasoline content regulations aim at reducing the local pollutants and dealing with the local air-pollution problems by enforcing the adoption of clean reformulated gasoline.

1.2.1 Local air pollutants from on-road vehicles and their relevant health impacts

The VOCs, NOx, CO, and PM generated by motor vehicles are four significant air pollutants that affect both ambient air quality and human health. On-road vehicles emit these pollutants into the air through fuel combustion and evaporation. When fuel is combusted under lack of oxygen content, the carbon contents in fuel do not burn completely and on-road CO emissions are emitted, especially during the wintertime. CO can cause health problems, varying from visual impairment and headaches to reduced work capacity, by hindering oxygen delivery to the body's organs and tissues.

VOCs (sometimes called hydrocarbons) are generated either through a vehicle's exhaust or through gasoline evaporation, while NOx is a product of high-temperature gasoline burning. Moreover, VOCs and NOx together react chemically to form ground-level ozone in the presence of sunlight. These are the precursors of ambient ozone, which is the primary component of smog and has negative health and environmental effects ranging from chest pain, cough, and throat irritation to reduced crop production.

PM2.5 with a diameter less than 2.5 micrometers is one of the main particulates emitted from motor vehicles mainly through tire wear and brake use. Due to its small size, it is believed to have the greatest negative effects on health, including asthma, breathing difficulty, and chronic bronchitis, especially for children and the elderly.

1.2.2 Overview of gasoline content regulation

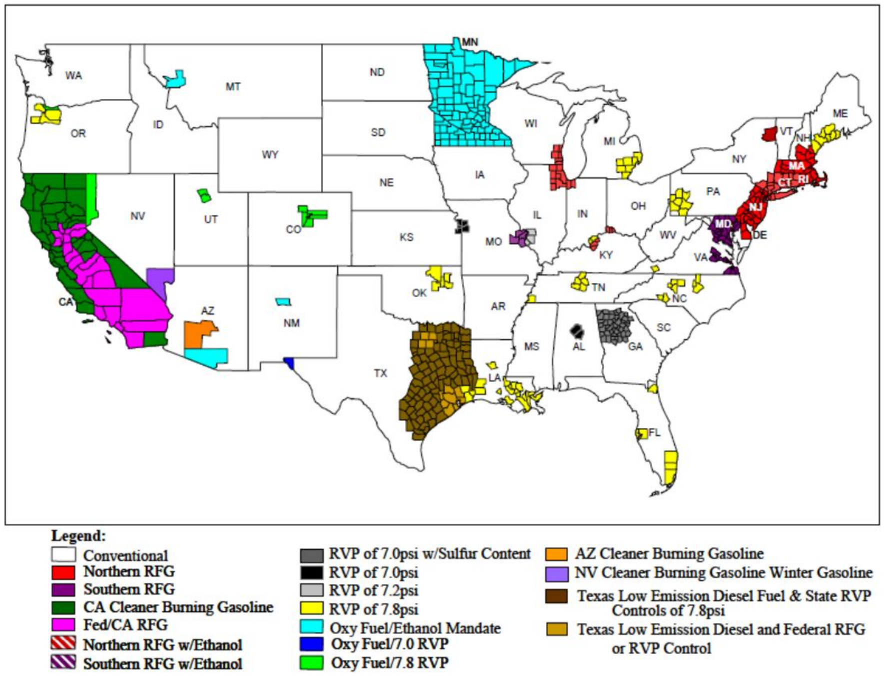
Prior to the Clean Air Act Amendments (CAAA) of 1990, the different gasoline types were distinguished by their octane grades. With the introduction of cleaner fuels required under the 1990 CAAA, gasoline is characterized by more dimensions of fuel properties, say oxygen contents and fuel additives. The burning of cleaner fuels rather than conventional fuels was chosen by the U.S. government as a policy instrument to improve air quality because cars and trucks are still a primary source of local air pollution. Figure 1 presents the different types of gasoline sold in the U.S. fuel market, as of May 2006. The figure shows that RFG, RVP, and OXY fuels, along with some state boutique fuels (say CARB and Arizona clean burning gasoline), are major clean fuels. The following subsections present a overview of the content regulations that prescribed these fuels.[6]

1.2.2.1 RFG program

The RFG program was first introduced in 1995, with Phase I covering 1995 through 1999 and Phase II being effective from January 1, 2000. Federally mandated areas are covered by the RFG program, but a state can also opt into this program to use the RFG within certain areas of a state. The program is targeted mainly at reducing the VOCs emissions during

[6] A good review on gasoline content regulation can be found in Brown et al. (2008), and more details can be found in the Code of Federal Regulations, 40 CFR Part 80, and EPA, EPAct Section 1541(c): Boutique fuels report to congress, 2006: `http://www.epa.gov/otaq/boutique/420r06901.pdf`.

Figure 1.1: U.S. gasoline requirements, as of May 2006



Source: EPAct Section 1541(c): Boutique Fuels Report to Congress, Figure 1, p. 7, 2006, available at `http://www.epa.gov/otaq/boutique/420r06901.pdf`.

the summer season of high ozone levels and the toxic air pollutants (TAP) throughout the whole year. Gasoline of lower volatility, measured by a lower RVP value, is used to limit the emission of VOCs.[7] Compared to conventional gasoline, the RFG fuel has lower RVP levels.

Figure 1 lists the areas covered by this RFG regulation. Particularly, the southern RFG regulated areas have more stringent RVP requirements relative to the northern areas because the temperature on average are higher for the former, which is prone to the formation of the RVP emissions. In addition, the RVP requirements has converted from low fuel RVP levels to explicit VOCs reductions as the RFG Phase I transits into the Phase II. Furthermore, the Phase II requires a higher reduction in the VOCs emissions in northern VOC-Control region, and higher reductions in NOx and TAP as well, compared to the Phase I. These differences reflect that RFG gasoline is required to achieve a better performance in terms of average emission reductions over time.

[7]The removal by refiners of the light component of the fuel, particularly butane, is a common approach for reducing the gasoline volatility because it is less costly to do so (see Auffhammer and Kellogg, 2011).

Moreover, the RFG fuel blend requires oxygen content greater than or equal to 2.0 by weight percent and benzene less than or equal to 1.0 by volume percent.[8] According to the EPA, the RFG program is a major gasoline content regulation as RFG is currently being used in 17 states and the District of Columbia, where non-attainment areas are federally mandated to use RFG, and attainment areas can opt into the program. RFG accounts for one-third of the gasoline sold in the United States. Table A1.1 in the Appendix provide more detailed information on the RFG regulation.

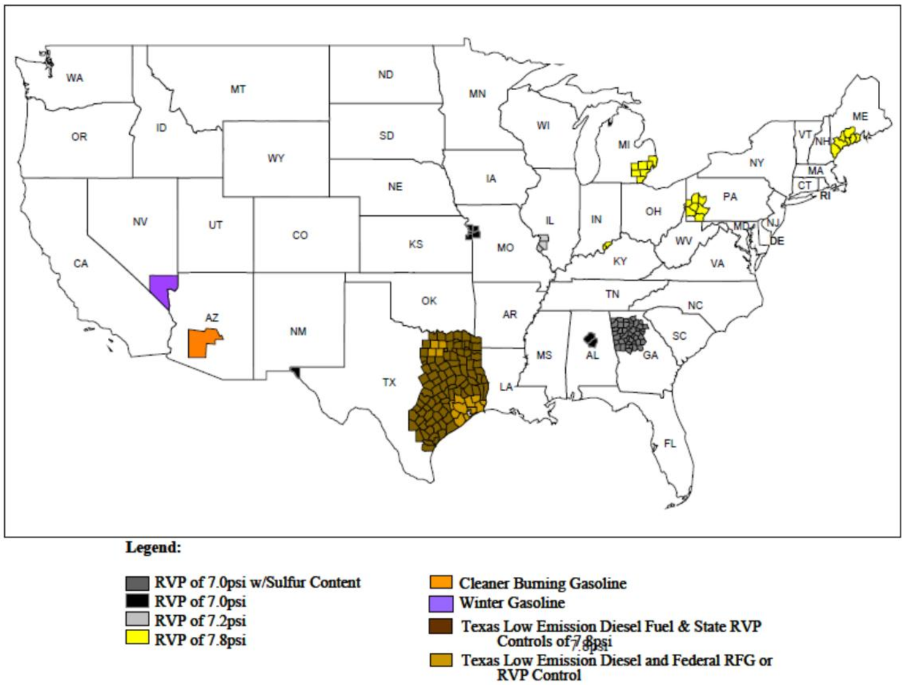
1.2.2.2 RVP program

The RVP regulation Phase I covered 48 states during the 1989 to 1991 summer periods. Limits on the RVP values of 10.5, 9.5, and 9.0 pounds per square inch (psi) were used across different areas in the United States, with a smaller number representing a stricter requirement. The RVP Phase II began in 1992 and required a bottom-line gasoline of 9.0 psi RVP across the nation, while a gasoline of 7.8 psi RVP applies to the southern ozone non-attainment states during the summer time. The RVP gasoline generally has a lower volatility than conventional gasoline and is used during the summer ozone season, typically from June 1 to September 15, when the ground-level ozone problem is serious.

The RVP regulation is either federally mandated or implemented through the SIPs. Figure 2 presents the RVP-regulated areas according to the RVP value. It also shows that the RVP gasoline is a major boutique fuel stipulated under the state fuel content regulations. In addition, some states implemented more stringent RVP requirements, say 7.0 and 7.2 psi, in the SIPs. The Guide on Federal and State Summer RVP Standards for Conventional Gasoline Only 2001, 2005, and 2010 lists the RVP limits by state and county. This regulation information is summarized in Table A1.2 of the Appendix.

[8]The requirements specified here are stated under per-gallon standards, while the corresponding requirements under averaged standards are slightly different.

Figure 1.2: State boutique fuel programs, as of May 2006



Source: EPAct Section 1541(c): Boutique Fuels Report to Congress, Figure 2, p. 8, 2006, available at `http://www.epa.gov/otaq/boutique/420r06901.pdf`.

1.2.2.3 Oxygenate Gasoline Program

The U.S. EPA has set upper CO limits of 35 parts per million (ppm) for a one-hour period and 9 ppm for an eight-hour period through the National Ambient Air Quality Standards (NAAQS). The OXY program starting on November 1, 1992 initially required 39 areas of CO non-attainment to use oxygenated gasoline. A minimum of 2.7 percent oxygen by weight was required for the non-attainment areas of the CO NAAQS in order to enhance fuel combustion and reduce CO emissions during the wintertime, typically from November 1 to February 28. Figure 1 also shows that the oxygenated (OXY) fuels are further distinguished by oxygenate type, indicating whether or not ethanol is required to be used as a fuel additive.[9]

Individual states are responsible for administering and enforcing the OXY program. The program applies to the larger of the Consolidated Metropolitan Statistical Area (CMSA) or

[9] Ethanol and methyl tertiary-butyl ether (MTBE) are two major additives used to produce oxygenated gasoline.

the Metropolitan Statistical Area (MSA) containing the CO non-attainment area(s). States may also implement the winter OXY fuel program beyond the scope required by the EPA or to some attainment areas. In addition, states may adjust the OXY gasoline-control periods and the oxygen-content weight of the fuel based on approval by the EPA. After a non-attainment area is re-designated as an attainment area, the oxygenated gasoline can still be used. Table A1.3 in Appendix provides more detailed information on the OXY regulation.

1.2.2.4 California Air Resources Board (CARB) reformulated gasoline

California adopted CARB reformulated gasoline on March 1, 1996.[10] This gasoline is used to reduce the emissions of VOCs, NOx, CO, and TAP. The gasoline formula is restricted based on the standards set for eight gasoline parameters: sulfur, benzene, olefins, aromatic hydrocarbons, oxygen, RVP, and distillation temperatures for the 50 percent (T-50) and 90 percent (T-90) evaporation points. The CARB gasoline contains oxygenated content ranging from 1.8 to 2.2 weight percent and has a RVP value within a narrow range from 6.6 to 7.0 psi during the summer season.

1.3 Literature Review

A wide range of government policies are implemented to address the issue of the externalities from motor vehicle usage. Fuel taxes and fuel-economy standards are well known as the two most important traditional fuel-conservation instruments Parry et al. (2007). These two instruments are well studied by early studies, while most recent economic analyses show an emerging trend towards evaluating the environmental impacts of the policies (or programs) that aim at solving the air pollution problem associated with vehicle usage, for example see Bento et al. (2011) and Mérel and Wimberger (2012).

[10] Phoenix, Arizona also adopted its state-specific content regulation, Arizona's Cleaner Burning Gasoline (AZCBG), on June 10, 1998, but it is not of interest in this paper because only one county adopted AZCBG.

The current study follows the trend and examines the emission-reduction effects of the U.S. federal and state gasoline-content regulations. The closely related studies are reviewed as following. Muehlegger (2006) builds a structural model to investigate how the price of gasoline is affected by the U.S. gasoline-content regulations during refinery outages, using data from the states of California, Illinois, and Wisconsin. He finds that a 5-7 cent per gallon price gap could be attributed to these regulations during the supply shock period. Using a control and treatment approach, Brown et al. (2008) find that the changes in the number of suppliers and geographic segmentation resulting from content regulation are important factors for explaining the price gap between regulated and unregulated areas. Chakravorty et al. (2008) argue that content regulation creates regulatory "islands" and thus increases the market power of firms, thereby contributing to the gasoline price gap. The current study differs from the previous studies which mainly focuses on the cost side of regulations.

Auffhammer and Kellogg (2011) first investigate the environmental effects, i.e., the benefit side, of the U.S. gasoline-content regulations. They examine how local air quality, measured by the ground-level ozone concentration levels, are affected by the introduction of the fuel regulations. Based on hourly ozone readings from the EPA's network of air-quality monitors across the United Stated from 1989 to 2008, Auffhammer and Kellogg (2011) construct the daily maximum ozone concentration level and daily 8-hour maximum. Using the difference in difference strategy, they find that the RFG and RVP programs do not significantly reduce ozone concentration levels, and thus, do not effectively improve air quality.

Auffhammer and Kellogg (2011) argue that the gasoline refiners under the RFG and RVP regimes have the flexibility to choose how to comply with federal gasoline requirements, which leads to the policy ineffectiveness of these two regulations. Particularly, the refiners in general choose to remove butane, a type of VOCs, but not the compounds which are more reactive in the formation of ground ozone, arising from the refiners' cost-minimizing behavior. The authors further conclude the local refiners' lack of flexibility to choose what kinds of harmful compounds in gasoline to remove accounts for California's significant air-quality improvement.

Table 1 shows that mobile fossil fuel combustion, solvent use, and industrial processes are three largest pollution sources of the VOCs emissions in 2002, accounting for 45.2%, 29.5%, and 12.1% of the total VOCs emissions, respectively; mobile fossil fuel combustion and stationary fossil fuel combustion account for 57.2% and 38.0% of the total NOx emissions, respectively; and mobile fossil fuel combustion is the largest source of the total CO emissions, with a proportion of 88.7 percent of the total emissions. Therefore, if motor vehicle exhaust is not the only source or is not the major source of VOCs and NOx emissions, the reduction in vehicle emissions and unrealized air quality improvement can occur at the same time.

Table 1.1: National emissions of VOCs, NOx, and CO by sources in 2002 (Gg[1])

Source/Pollutant	VOCs	*ratio*	NOx	*ratio*	CO	*ratio*
Stationary Fossil Fuel Combustion	1,147	*0.076*	7,542	***0.380***	3,961	***0.043***
Mobile Fossil Fuel Combustion	6,771	***0.452***	11,352	***0.572***	82,063	***0.887***
Oil and Gas Activities	348	*0.023*	118	*0.006*	153	*0.002*
Waste Combustion	333	*0.022*	149	*0.008*	3,294	***0.036***
Industrial Processes	1,818	***0.121***	649	***0.033***	2,304	*0.025*
Solvent Use	4,420	***0.295***	3	*0.000*	44	*0.000*
Field Burning of Agricultural Residues	NA	*NA*	33	*0.002*	706	*0.008*
Waste	158	*0.011*	3	*0.000*	15	*0.000*
Total	14,996		19,849		92,541	

Notes: 1. Gg refers to gigagrams. 2. The proportions of three largest sources of each pollutant are highlighted. Source: Derived from the U.S. EPA, Inventory of U.S. greenhouse gas emissions and sinks: 1990-2002.

Particularly, the current study finds the policy ineffectiveness of the gasoline content regulations on reducing the emissions from off-road engines and vehicles. Thus, the current study also differs from Auffhammer and Kellogg (2011) because, by examining the pollution reduction effect of the regulations, it provides other possible explanation why ground ozone levels in some regulated areas do not drop significantly.

The current paper also empirically examines whether or not the OXY program helps reduce vehicle CO emissions, and whether or not the gasoline content regulations affect the emissions from off-road sources. Auffhammer and Kellogg (2011) do not address these issues in their study.

1.4 Data

The National Emissions Inventory (NEI) provides us with an estimated emissions for volatile organic compounds (VOCs), nitrogen oxides (NOx), and carbon monoxide (CO) by emissions sources. The U.S. EPA prepares the NEI data primarily based on emission estimates and emission model inputs provided by State, Local, and Tribal air agencies and supplemented by data developed by the EPA. One of the intended purposes of preparing the NEI is to provide a starting point for rule development, past and ongoing examples include Non-road Rule, Transport Rule, and Clear Skies, etc..

The emissions in the NEI refer to the amounts of pollutants emitted into the air during a year. The NEI summarizes the annual emissions according to the emission sources and is available at a county level for all fifty states plus the District of Columbia, Puerto Rico, and the Virgin Islands in the United States.[11] The emissions data are available for 3,140 counties for 1990, and from 1996 to 2002, for a total of 8 years.[12]

Moreover, the NEI classifies the emission sources of the pollutants based on 14 “Tier-1” categories.[13] Specifically, the category “on-road vehicles” refers to motorized vehicles of normal

[11] Puerto Rico and the Virgin Islands are omitted in the current study because of missing data.

[12] To my best knowledge, the clean fuel regulations are the only environmental regulations for this time period. If some other regulations were implemented and these regulations affected vehicle fleet across the nation in a same way, the D-in-D approach would still provide an unbiased policy effect.

In addition, Auffhammer and Kellogg (2011) do not use data beyond 2003 in their study though the data are available. They argue that both federal and California gasoline regulations began to impose new sulfur content standards in 2004. Using data beyond 2003 could confound the estimated effect of RVP, RFG, and CARB regulations because these new standards could affect the emissions of NOx. The sample period for the current study is up to year 2002, our empirical results should not be affected by the sulfur content regulations.

[13] Include fuel combustion from electric utilities, industrial processes, and other sources, chemical and allied product manufacturing, metals processing, petroleum and related industries, other industrial processes, solvent utilization, storage and transportation, waste disposal and recycling, on-road vehicles, non-road engines and vehicles, natural sources, and miscellaneous.

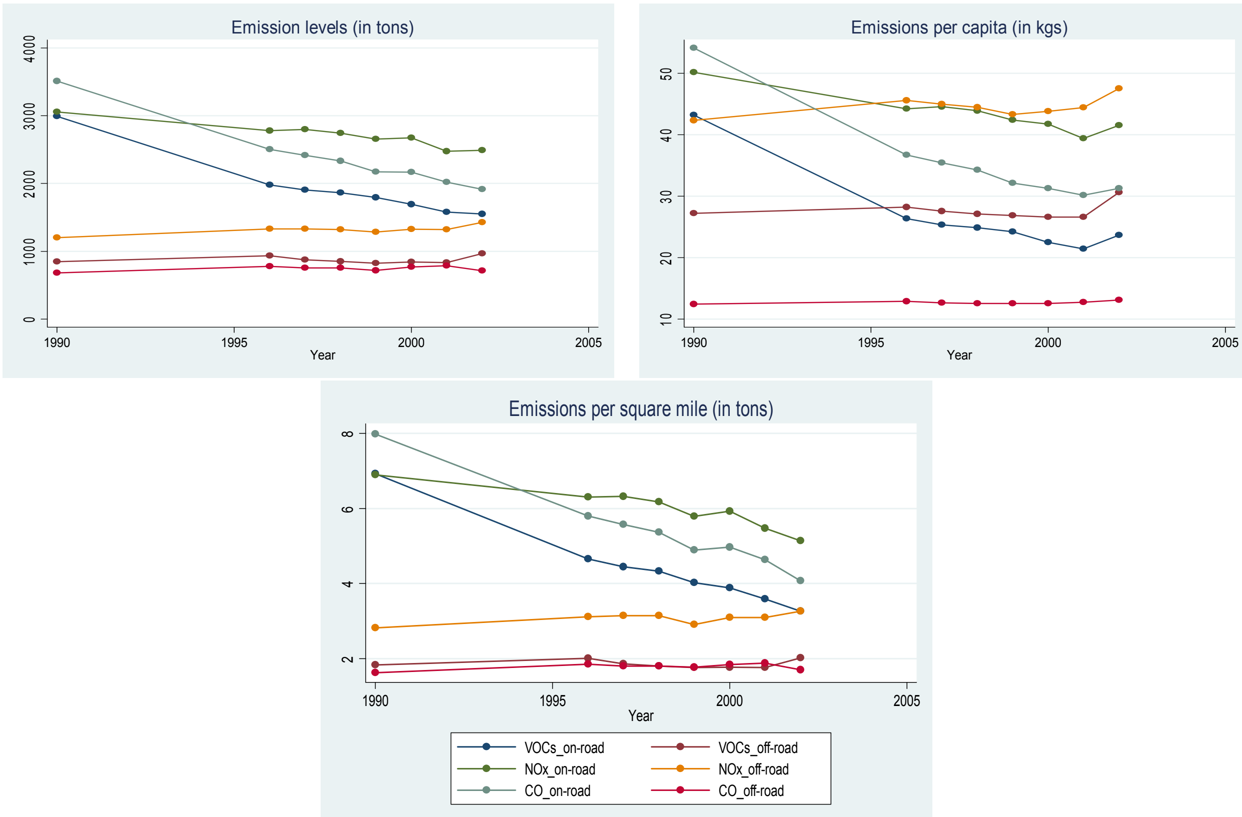
operation on public roadways, including passenger cars, motorcycles, minivans, sport-utility vehicles, light-duty trucks, heavy-duty trucks, and buses. The non-road sources include the following general equipment categories: agricultural, airport support, light commercial, construction and mining, industrial, lawn and garden, logging, pleasure craft, railroad, and recreational equipment.

More spefically, county on-road emissions are estimated by multiplying county VMT with appropriate emission factors. The NEI documentation states that county VMT is obtained based on the data supplied by the Federal Highway Administration (FHWA). Essentially, county VMT is determined by travel volume occurred within the county but not by where a vehicle is registered and the vehicle owner's residential address. Particularly, the FHWA divides VMT among multi-state urban areas according to their portions in each state. Thus, the issue of commuting zones should not be a concern to accurately estimate county on-road emissions.

In this study, the emissions of VOCs, NOx, and CO are more focused because these pollutants are addressed by the clean fuel regulations. In addition, the on-road VOCs, NOx, and CO in the NEI are exhaust and evaporative VOCs, exhaust NOx, and exhaust CO, respectively. The first panel in Figure 3 presents the mean county emission levels by pollutant from 1990 to 2002. The mean levels for VOCs, NOx, and CO are decreasing overtime for the on-road vehicles, as a result, the means of per capita emissions and emission densities also exhibit a decreasing trend as well (also see Figure 3). In contrast, the figure shows that the pollution from off-road engines and vehicles tend to increase during the same period, no matter which measure of pollution is used.

One thing needed to point out is that the on-road emissions in the NEI are estimated data. Real vehicle emissions are definitely better than the estimated emissions to use in order to evaluate the effect of the gasoline content regulations. However, it is impossible to collect real values for on-road fleet, even for a single vehicle. The current study controls for the factors that could significantly affect the on-road vehicle emissions. After removing the effect

Figure 1.3: 1990-2002 county emission trends, on-road vs. off-road



Note: the emissions of CO is scaled by 1/10.

of these factors on the on-road emissions, the difference in the reduction of emssions between control and treatment groups could be a reflection of the regulation effect. However, if one or more important control variables are not available, the estimated regulation effect could be biased. Moreover, the accuracy of the estimated policy effect also are dependent on the credibility of the NEI dataset.

When estimating the pollution emissions from the on-road sources, the NEI first calculated the vehicle miles traveled (VMT) by county, roadway type, and vehicle type for each year, and then multiplied the VMT by an appropriate emission factor in the form of grams per mile.[14] The emission factors for VOCs, NOx, and CO used in the NEI were estimated from

[14]The roadway types in the NEI are classified into twelve types. The six rural roadway types are principal arterial-interstate, other principal arterial, minor arterial, major collector, minor collector, and local. The six small urban and urban roadway types are principal arterial-interstate, principal arterial-other freeways and expressways, other principal arterial, minor arterial, collector, and local.

the EPA's MOBILE computer software, which accounts for the emission-reduction effects of various on-road control programs on their targeted pollutants, such as the Inspection and Maintenance (I/M) program, the RFG fuel program, and the National Low Emission Vehicle (NLEV) program. In other words, the effects of pollution-control equipment and regulatory operating restrictions are taken into account to estimate the emissions, which is called the "estimated emissions with rule effectiveness" according to the EPA. Thus, the estimated emissions from the NEI could accurately represent the local emissions of air pollutants and reflect the effects of local emission-control policies.

The population data used in the current paper were obtained from the time series of the U.S. Census Bureau intercensal estimates at a county level. In addition, the data on monthly means of daily maximum air temperature in degrees Celsius (^0C) and monthly means of daily minimum air temperature (^0C) are from Historical Climate data (1940-2006) for the conterminous United States at the county spatial scale based on PRISM climatology.

1.5 Empirical strategy and regression results

1.5.1 Strategy

The difference-in difference (D-in-D) strategy is employed to identify the environmental effects of the fuel content regulations. In order to perform the empirical analysis, the treatment and control groups need to be determined. Three treatments are used:

1. RVP phase II with summer RVP of 7.8 psi or lower (federally mandated and SIPs mandated counties, 1992 onward).

2. Federal RFG with summer RVP limit level of 7.1 psi for VOC-control region I, and 8.0 psi for VOC-control region II on average standard. This treatment also requires a minimum 2.0 weight percent of oxygen content (federally mandated and opt-in counties, 1995 onward).

3. Winter OXY fuel program (CO non-attainment areas, November 1, 1992 onward).

These three treatments were chosen because they are the current major clean fuel regulations in the United States. A county is classified into a relevant treatment group if it had been adopting or had ever adopted this treatment but quit later during the sample period. All counties across the United States are allocated into three treatment groups and one control group in which a county never adopts any of the clean fuel regulations.

The CARB fuel regulation is not examined in this study, as the entire state of California started implementing the CARB program in 1996, and there are no variations in fuel regulations within the state. The counties in this state would be categorized into the same treatment group and dropped when running a state-fixed effect model. In addition, the Arizona clean burning gasoline (AZCBG) program is not studied in the analysis because Maricopa is the only county adopting this program and has clean fuel regulation overlaps as well: Phoenix (the county seat of Maricopa) used the winter OXY fuel from 1989/1990 winter, adopted the RVP through 1992 to 1997, adopted the RFG in 1997 and 1998, and converted from the RFG to the AZCBG on June 10, 1998. Thus, the emission reductions cannot be divided among the different policies.

In order to implement the D-in-D strategy, the pre-regulation year and post-regulation year also need to be defined. They are defined accordingly dependent of which one of the following three situations occurs for a treated county. First, a county may have already used cleaner gasoline in the year 1990. Only 6 cities started using the winter OXY fuel in the 1989/1990 winter season: Denver, Colorado; Reno and Las Vegas, Nevada; Tucson and Phoenix, Arizona; and Albuquerque, New Mexico.[15] In this case, the pre-regulation year does not exist because the first sample year in this study is 1990. Thus, the counties corresponding to the 6 cities above will be dropped from the study.

[15]Denver Co., Washoe Co. and Clark Co., Pima Co. and Maricopa Co., and Bernalillo Co. match the six cities above, respectively. Source: EPA, Gasoline composition regulations affecting LUST sites, EPA 600/R-10/001, Jan 2010.

Second, a county may have used or just start using cleaner gasoline in 1996 but not 1990. This situation applies to most of treatment counties because both the OXY winter fuel program and the RVP phase II started in 1992, and the RFG and CARB were first introduced in 1995 and 1996, respectively. Because the data contain a missing interval from 1991 to 1995, the year 1990 is used as the pre-treatment year and 1996 is used as the post-treatment year for these counties. Empirically, the emission-reduction effects are examined between 1990 and 1996 for these counties.

Third, it is also possible that a county adopted the clean fuel regulations later than 1996. Now, the year first introducing the regulations is defined as the post-treatment year and one year earlier than the post is the pre-treatment year. Keeping the pre-treatment year unchanged, this paper empirically examines how the policy effects change as the temporal span of adopting a certain type of clean fuels extends.

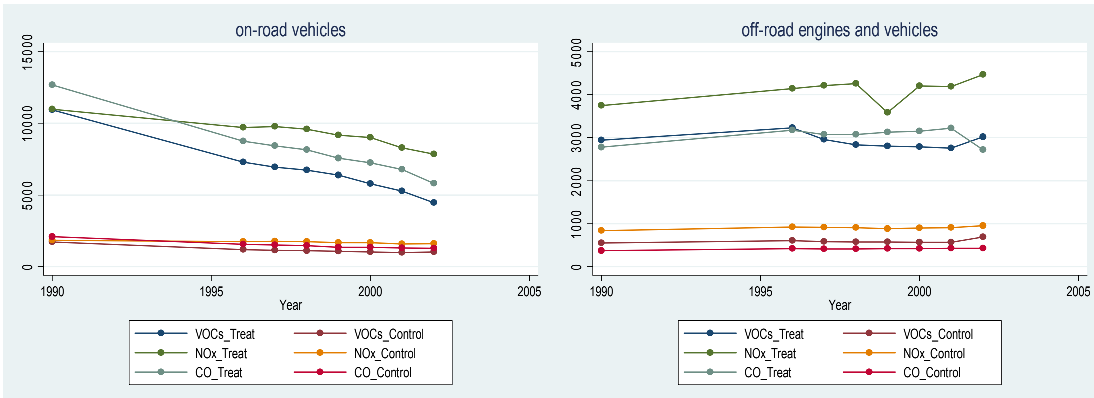
Table 1.2: Descriptive statistics by year (policy-related)

	Number of counties							
Year	1990	1996	1997	1998	1999	2000	2001	2002
				RFG regulation				
Switch in	0	163	1	0	5	0	0	0
Purified	*0*	*130*	*0*	*0*	*0*	*0*	*0*	*0*
Switch out	0	6	0	1	7	0	0	0
Purified	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
				RVP regulation				
Switch in	0	95	0	7	19	94	0	0
Purified	*0*	*83*	*0*	*7*	*12*	*94*	*0*	*0*
Switch out	0	52	1	0	5	0	0	0
Purified	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
				OXY regulation				
Switch in	6	76	0	0	0	0	0	0
Purified	*0*	*21*	*0*	*0*	*0*	*0*	*0*	*0*
Switch out	0	40	0	19	13	16	1	1
Purified	*0*	*0*	*0*	*0*	*0*	*2*	*1*	*1*

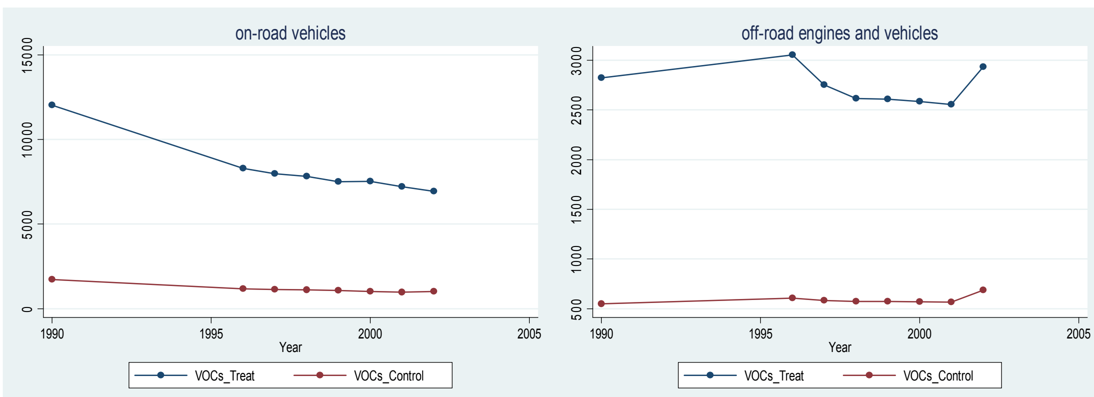
Note: Only 10 counties in Minnesota were incorporated into the OXY-treated group in this study according to the documentation for the on-road national emissions inventory (NEI) for base years 1970-2002, though Minnesota adopted a statewide oxygen mandate throughout the year beginning on October 1, 1997.

Table 2 presents the number of counties that switch into each clean fuel regulation over 1990-2002. However, these treatment counties still need to be purified. First, a county simultaneously regulated by two or more regulations in a post-treatment year will be dropped from the study, as it is impossible to partition the emission reductions among the corresponding policy regulations in the overlap year. Second, a county converting from one clean fuel regime to the other will also be dropped when examining the later policy's effects, as this county is not unregulated in the pre-treatment year. After purification, the current study investigates 130 treated counties that adopted the RFG in 1996, 83, 7, 12, and 94 treated counties that adopted the RVP in 1996, 1998, 1999, and 2000, respectively, and 21 counties that adopted the OXY fuel program in 1996. For more information on the scope of these treated counties, see Tables A1.4 to A1.7 in the Appendix.

Figure 1.4: 1990-2002 mean emission trends for VOCs, NOx, and CO, regulated group vs. control group (tons)[1]



(a) RFG regulation[2]



(b) RVP regulation

(c) OXY regulation

Notes: 1. The emission trends for the treatment groups are calculated based on the purified 1996-switch-in counties. 2. The magnitude of CO emissions is scaled by 1/10 in Figure 4(a).

Based on the scopes of the purified 1996-switch-in counties, the mean emissions are calculated and drew in Figure 4 for both the regulated and control counties. With respect to on-road vehicles, it can be observed that the emissions of all pollutants of interest exhibit decreasing trends over the period of 1990 to 2002, for both the regulated and control groups no matter which regulation is examined. In contrast, the emissions of off-road engines and vehicles tend to increase for two groups within the same period. More importantly, Figure 4 shows that the on-road emissions from the regulated group decrease faster than the emissions from the control group across different regulations.

Now, the goal of the current study becomes more specific. For the RFG-treated counties, the reductions in VOCs, NOx, and CO are compared with the corresponding reductions in the control, because the RFG regulation is intended to reduce these three pollutants. The reductions in VOCs in the RVP-treated group are also compared with those in the control, because the RVP regulation is aimed at reducing the VOCs emissions. In addition, the reductions in CO in the winter OXY-treated group are compared with those in the control, because the OXY regulation is used to control the CO emissions. Moreover, the later empirical analysis outcome is obtained based on two separate treatment groups: the counties that switched into a clean fuel regime in 1996 and counties that switched into a clean fuel regime later than 1996.

To evaluate the policy effects, the basic empirical regression is estimated as:

$$\begin{aligned} Pollu_{c,t} = cons + a \cdot Pop_{c,t} + b \cdot Popdn_{c,t} + c \cdot Incper_{c,t} + d \cdot Tempt_{c,t} \\ + \alpha \cdot Treat_c + \beta \cdot dafter + \gamma \cdot (Treat_c \cdot dafter) + \mu_i \cdot State_i + \varepsilon_{c,t} \quad (1.1) \end{aligned}$$

where $Pollu_{c,t}$ and $Pop_{c,t}$ are annual emissions (in tons) and population for county c at year t.[16] Population is a key factor to explain the pollution levels, as a larger population means

[16]The D-in-D model can also be set up with different ways, for example, see Auffhammer and Kellogg (2011). Ttheoretically, the alternative way of setting up D-in-D model will present same estimation results as

more vehicle miles traveled, and thus more pollution. The correlation coefficients between VOCs, NOx, and CO, and population are 0.918, 0.959, and 0.914, respectively. In addition, $Popdn_{c,t}$ and $Incper_{c,t}$ represent population densities and income per capita, respectively. Areas with higher population densities tend to be crowded and characterized by good public transit services, and thus vehicle driving may be restricted and population densities could negatively affect the vehicle pollution. In contrast, people with higher per capita income levels are more likely to own a vehicle and drive more, which results in more pollution.

$Tempt_{c,t}$, monthly average maximum or minimum temperature, is controlled in the regression as well. When examining the pollution reduction effects of the regulations on the VOCs and NOx, average maximum temperature in July is controlled for to reflect the fact that vehicles produce more evaporative emissions for the VOCs and NOx in the summer time. However, the average minimum temperature in January is controlled for when examining the CO emission reduction effects because carbon contents in gasoline tend to burn incompletely to generate the CO emissions in the cold winter time.

$State_i$ is a dummy variable representing state i and is used to absorb state-specific effects.[17] After controlling for these variables, the differential in emissions deductions between the regulated counties and control counties could be attributed to the policy-related variables. $Treat_c$ is a binary variable indicating whether a county falls into a certain type of treated group or not; more specifically, $Trfg$, $Trvp$, and $Toxy$ are used to represent the RFG-treated group, RVP-treated group, and OXY-treated group, respectively, while $Treat_c$ equal to 0 represents the control, and $dafter$ is a binary variable indicating the pre-treatment or post-treatment year. For the counties that adopted the clean fuel content regulations in 1996, $dafter$ equals 0 when t=1990 and 1 when t=1990. $\varepsilon_{c,t}$ is an unobserved disturbance.

In addition, the coefficients in the model have the following interpretations:

shown by the current study.

[17] The NEI dataset has emission values for over 3000 counties, as a result, using county fixed effect rather than state fixed effect will cause the regression inestimable.

$$\alpha = E[P_{c,t}|Treat_c = 1,\ dafter = 0] - E[P_{c,t}|Treat_c = 0,\ dafter = 0]$$

$$\beta = E[P_{c,t}|Treat_c = 0,\ dafter = 1] - E[P_{c,t}|Treat_c = 0,\ dafter = 0]$$

$$\begin{aligned}\gamma = \{&E[P_{c,t}|Treat_c = 1,\ dafter = 1] - E[P_{c,t}|Treat_c = 1,\ dafter = 0]\} \\ &-\{[P_{c,t}|Treat_c = 0,\ dafter = 1] - E[P_{c,t}|Treat_c = 0,\ dafter = 0]\},\end{aligned}$$

where α measures the difference in mean pollution levels between the treated and the control in the pre-treatment period; β measures the difference in mean pollution levels between the pre-treatment and post-treatment periods for the control; and γ is the D-in-D estimator that reflects the policy effects.[18]

For the counties that adopt the clean fuel later than 1996 (the RVP-treated counties only), the counties that switch into the RVP regulation in 1998, 1999, and 2000 are initially treated as one group. Thus, a generalized treatment effect across different switch-in groups is obtained by estimating the equation (1). However, it may argue that the regulation effects of interest could vary across switch-in groups. This assumption is examined by using the following regression specification:

[18] The lack of data for the period from 1991 to 1995 would result in an upper estimate of the policy pollution reduction effect by using the year 1990 as the only pre-treatment year, provided that the treatment and control groups had a same emission reduction trend in the absence of the gasoline content regulations.

$$
\begin{aligned}
Pollu_{c,t} = cons &+ \sum_{j=1}^{3}(a_j \cdot Pop_{c,t} \cdot P_j) + \sum_{j=1}^{3}(b_j \cdot Popdn_{c,t} \cdot P_j) + \sum_{j=1}^{3}(c_j \cdot Incper_{c,t} \cdot P_j) \\
&+ \sum_{j=1}^{3}(d_j \cdot Tempt_{c,t} \cdot P_j) + \sum_{j=1}^{3}(\alpha_j \cdot Treat_c \cdot P_j) + \sum_{j=1}^{3}(\beta_j \cdot dafter \cdot P_j) \\
&+ \sum_{j=1}^{3}(\gamma_j \cdot Treat_c \cdot dafter \cdot P_j) + \sum_{j=1}^{3}(\mu_j \cdot State_i \cdot P_j) + \sum_{j=1}^{2} P_j + \varepsilon_{c,t} \qquad (1.2)
\end{aligned}
$$

where $P_1 - P_3$ are dummies for 1998, 1999, and 2000 RVP-switch-in groups, respectively.

Moreover, some counties might have withdrawn from the regulation later on. In this case, the study also examines whether or not the pollution reduction effects disappear once the regulation program ceases within this county. However, a pre-treatment year now is redefined as the last year when a county is regulated by one fuel regulation. Meanwhile, it is required that there is no policy overlap in a pre-treatment year and a county quit from the related regulation but not transit into any other fuel regulation in a post-treatment year.

Table 2 also shows the number of counties that switch out each fuel regulation by calendar year. Purified by the two requirements listed above, the RFG and RVP switch-out counties are dropped from the study, while 2, 1, and 1 counties that switch out of the OXY regime in 2000, 2001, and 2002, respectively, are left to be investigated. For the scope of these switch-out counties, see Table A1.7 in the Appendix. A generalized switch-out effect is estimated by the equation (1) and separate switch-out effects also are estimated by the equation (2) in which $P_1 - P_3$ now refer to 1999, 2000, and 2001 OXY-switch-out groups, respectively.

1.5.2 Empirical Results

D-in-D approach can provide an unbiased estimate of policy effect provided that the control and treatment groups have a similar emission trend in pre-treatment period. However, 1996 is the only pre-treatment year available to us, so it is impossible to examine the similarity of pre-treatment trend given the database used in the current study. However, the NEI dataset contains pollution data for 7 pollutants and 14 emission sectors. By comparing the emissions of different pollutants and from the sources other than on-road and off-road sectors, the relative changes in these emissions between the treatment and contrl groups over the period 1990 to 1996 could provide some clues on whether or not the assumption of the similar trend holds.[19] Moreover, the relative changes can also be estimated by using the regression (1). If the similarity assumption holds, the estimate of treatment effect should be statistically insignificant.

The emssions from fuel combustion-industrial are chosen to compare between the treatment and control groups because fuel combustion-industrial may reflect the local economic activities and produce all 7 pollutants.[20] With respect to the source of fuel combustion-industrial, Table 3 below shows that the relative changes in the emissions of CO, NOx, VOCs, Ammonia (NH3), PM10 and PM2.5 are statistically insignificant, but not Sulfur dioxide (SO2). This finding implies that the similarity assumption may hold.

Table 1.3: The relative changes in emissions between the treatment and control groups (tons)

	fuel combustion-industrial						
Pollutant	CO	NOx	VOCs	SO2[1]	NH3	PM10	PM2.5
Relative changes	52.69	-634.49	28.05	-1428.74	16.04	-18.23	-10.13

Note: 1. Only the estimate on SO2 is statistically significant at a 10 percent confidence level. 2. With respect to SO2, NH3, PM10, and PM2.5, the estimates are obtained by using the regression (1) while without including the temperature variables, however, whether or not include these variable only marginally affect the estimation results.

Tables 4 and 5 present the estimated environmental effects of the different gasoline-content regulations from on-road vehicles. For the counties that adopted the RFG in 1996, Table 4 shows that county population and income per capita significantly affect emission levels: a county with higher population and income levels has a higher volume of vehicle usage and

[19] The current study assumes that the gasoline content regulations have no impact on the emissions from the other sectors.

[20] Fuel combustion-industrial refers to the combustion of coal, oil, gas and other fuels for industrial purposes.

amount of vehicle pollution compared to a county with less population and income levels. However, it seems that the temperature and population densities variable may not explain the county's aggregate pollution levels well.

The estimates on $Trfg$ are used to measure the differences in the mean pollution levels between the RFG-treated group and the control in the pre-treatment year. The differences are significant and estimated as 2,016.7 tons in the mean VOCs emissions, 1,256.6 tons in the mean NOx emissions, and 19,744.1 tons in the mean CO emissions. This means that the pollution levels for the RFG-treated counties in the pre-regulation year are significantly higher than those for the untreated counties. This finding is consistent with the fact that the clean fuel regulations in general were adopted by the severely polluted areas to solve their pollution problems.

Regarding emission levels, Table 4 also shows that the estimates on $dafter$ are all significantly negative, which means that the average emissions gradually decrease over time for the unregulated counties. The pollution reductions can be attributed to the contribution of adopting other regulations that potentially affect vehicle usage and fuel consumption, say higher fuel economy requirements.

Now, turn to the RFG-treatment effects. The estimates on $Trfgdafter$ in Table 4 are all statistically significant across the three vehicle pollutants. The reductions from the RFG are 3,884.6 tons (or 35.5%) in the mean VOCs emissions, 1,860.4 tons (or 16.9%) in the mean NOx emissions, and 43,181.4 tons (or 34.1%) in the mean CO emissions, together valued around 37.83 million US dollars at county level.[21][22] However, the table illustrates that RFG gasoline does not effectively affect the emissions per capita but the emission densities with a significant decrease of 14.2, 6.4, and 148.7 tons per square mile for the pollutants VOCs, NOx, and CO, respectively. Nevertheless, the current study also shows policy overlap would

[21]The mean VOCs, NOx, and CO levels in the pre-treatment year are 10,927.9, 10,985.2, and 126,675.7 tons, respectively.

[22]Following Anweiler and Gulati (2011), Hydrocarbon (HC), NOx, and CO were valued at approximately \$3.5, \$3.5, and \$0.5 CAD per kilogram in 2010 prices, respectively. The average annual exchange rate between the USD and CAD was 1.02993904 in 2010.

Table 1.4: RFG effects, on-road vehicles (tons)

RFG	VOCs	NOx	CO	VOCs	NOx	CO	VOCs	NOx	CO
	Emission levels (tons)			Emissions per capita (kgs)			Emissions per square mile (tons)		
Pop	0.0260***	0.0278***	0.302***	-5.56e-06***	-1.36e-05***	-8.01e-05***	-1.95e-07	-2.62e-07	-9.44e-07
	(1.68e-03)	(1.09e-03)	(0.0188)	(1.77e-06)	(4.63e-06)	(2.53e-05)	(3.03e-06)	(2.65e-06)	(3.26e-05)
Pop_dn	-0.432*	-0.631***	-4.994	-4.84e-04*	-1.80e-03***	-8.43e-03**	0.0235***	0.0246***	0.274***
	(0.252)	(0.242)	(3.077)	(2.80e-04)	(5.52e-04)	(3.68e-03)	(2.56e-03)	(2.48e-03)	(0.0293)
Inc_per	0.0519***	0.0611***	0.708***	-7.01e-05	-4.47e-04**	-2.56e-03	1.55e-04***	1.98e-04***	1.98e-03***
	(0.0160)	(0.0117)	(0.184)	(1.10e-04)	(2.27e-04)	(1.76e-03)	(5.91e-05)	(5.41e-05)	(6.82e-04)
Tmax_7	10.89	19.19*		-0.0798	0.248		0.0758***	0.0514***	
	(11.06)	(9.843)		(0.186)	(0.338)		(0.0213)	(0.0185)	
Tmin_1			96.49			-8.800***			0.159
			(116.7)			(1.519)			(0.164)
Trfg	2016.7***	1256.6***	19744.1***	-2.376	-2.422	-23.71	10.62***	7.180***	107.8***
	(477.0)	(339.6)	(5168.5)	(1.493)	(1.892)	(18.77)	(2.144)	(1.536)	(22.47)
dafter	-832.7***	-426.2***	-8498.4***	-16.55***	-3.378***	-206.4***	-1.606***	-1.056***	-16.85***
	(65.57)	(50.79)	(630.2)	(0.621)	(1.232)	(12.62)	(0.238)	(0.216)	(2.841)
Trfgdafter	**-3884.6*** **	**-1860.4*** **	**-43181.4*** **	**1.484**	**-2.062**	**4.557**	**-14.21*** **	**-6.405*** **	**-148.7*** **
	(507.8)	**(408.8)**	**(5760.9)**	**(1.193)**	**(1.837)**	**(15.61)**	**(2.690)**	**(2.310)**	**(29.61)**
const	30.24	-293.9	2445.6	49.12***	48.80***	606.1***	-2.878***	-2.587***	-8.309
	(456.3)	(378.0)	(2286.4)	(6.352)	(11.57)	(26.61)	(1.086)	(0.927)	(8.389)
r2	0.928	0.952	0.929	0.339	0.116	0.265	0.877	0.915	0.887
n	5526								

Notes: 1. The numbers in parentheses are robust standard errors, which are estimated by using the Huber-White sandwich estimator. Robust standard errors are estimated while accounting for the issues of heterogeneity and lack of normality and are applied to all empirical results in this study. 2. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

result in higher pollution reductions, for more details, see Table A1.8 and A1.13 in Appendix.

Table Tab. 1.5 shows that, regardless of which regulation is concerned, the emissions per capita of the control areas are higher in the pre-treatment year, 1990, compared to those of the treatment areas. In addition, population grows more slowly in the control areas, which leads to a relatively higher level of emissions per capita in the post-treatment year, 1996, again compared to the treatment group. As a result, it is hard to predict the relative changes in emissions per capita between the two groups, which may possibly explain the insignificant effect of the regulations on emissions per capita.

Table 1.5: Population growth and emssions per capita (g) by control and treatment groups

Regulations	Pollutant	population growth rate		emissions per capita (g)			
		treatment	control	treatment		control	
				before	after	before	after
RFG	VOCs	9%	6%	34	19	44	27
RVP	VOCs	11%	6%	37	23	44	27
OXY	CO	15%	6%	465	281	555	383

With respect to the counties that adopted the RVP regulation in 1996, Table Tab. 1.6 shows that the RVP significantly reduce the VOCs emissions by 3,679.6 tons (or 30.6%), valued at 11.68 million US dollars.[23][24] For the 1998-switch-in, 1999-switch-in, and 2000-switch-in counties, the treatment effects obtained from the generalized specification are all negative. Moreover, the estimates on the variables $TrvpdafterP1$ $TrvpdafterP2$ and $TrvpdafterP3$ in the table present the separate policy effects across the RVP switch-in groups. It shows that the treatment effects are negative but not statistically significant for the 1998 switch-in group. However, the 4-year effects for the 1999-switch-in group and the 2-year and 3-year effects for the 2000-switch-in RVP group become significant and the magnitudes of the estimated policy effects increase over time. In general, it is observed that the RVP treatment effects tend to become stronger as the temporal scope of this study is expanded. Regarding the

[23]The VOCs level in the pre-treatment year is 12,029.2 tons.

[24]With respect to the RVP and OXY regulations, this study only presents the estimated treatment effects due to the limited space. Full regression results can be obtained by request.

effects of the RVP regulation on on-road emissions per capita and emission densities, see Table A1.9 in the Appendix.

Table 1.6: RVP and OXY effects, on-road vehicles

RVP	1996-switch-in	1998, 1999, and 2000-switch-in				
	1990-1996	1-year-in	2-year-in	3-year-in	4-year-in	5-year-in
	VOCs emission levels (tons)					
		Generalized effects				
Trvpdafter	-3679.6***	-66.51	-183.0**	-450.8***	-671.5*	-1389.1
	(575.4)	(60.12)	(73.53)	(118.7)	(397.0)	(1127.5)
		Separate effects				
TrvpdafterP1		-286.0	-708.6	-1125.1	-1407.3	-1389.1
		(709.2)	(759.4)	(865.2)	(892.0)	(1127.5)
TrvpdafterP2		-16.11	-35.84	-26.83	-246.7*	
		(125.1)	(121.7)	(122.0)	(140.8)	
TrvpdafterP3		-63.91	-159.3**	-492.4***		
		(60.68)	(69.36)	(121.9)		
r2	0.93	0.96	0.96	0.95	0.95	0.94
n	5446	16072	16072	16072	10602	5296

OXY	1996-switch-in	2000, 2001, and 2002-switch-out		
	1990-1996	1-year-out	2-year-out	3-year-out
	CO emission levels (tons)			
		Generalized effects		
Toxydafter	-35714.6***	4032.2	8629.8	6271.7
	(8819.4)	(8979.0)	(14054.9)	(15768.0)
		Separate effects		
ToxydafterP1		5916.9	2160.8	6271.7
		(17726.5)	(17502.9)	(15768.0)
ToxydafterP2		-637.5***	21690.7***	
		(138.7)	(196.8)	
ToxydafterP3		4622.2***		
		(185.2)		
r2	0.93	0.95	0.95	0.95
n	5233	15854	10570	5286

Notes: 1. The numbers in parentheses are the standard errors. 2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

In terms of the OXY regulation, the counties that adopted the OXY in 1996 experience a faster reduction of the CO emissions compared to the control counties. The treatment effects are 35,714.6 tons (or 35.4%) of CO reductions, valuated at 16.20 million US dollars at county level (also see Table Tab. 1.6).[25] For more information related to the OXY effects

[25] The CO level in the pre-treatment year is 100,948.4 tons.

on on-road emissions per capita and emission densities, see Table A1.10 in the Appendix.

So far, the switch-in effects have been evaluated. However, it can also provide some clues about the effectiveness of the fuel regulations by examining if the treatment effects disappear once a county stops using clean fuels. As argued earlier, the counties that switch out of the RFG and RVP regulations are dropped from this study. For the 2000-switch-out, 2001-switch-out, and 2002-switch-out counties, the OXY regulation effects cease quickly because none of the generalized estimates on Toxdafter in Table Tab. 1.6 is significantly negative. Regarding the separate policy effects, the OXY regulation only helps reduce the aggregate CO emissions for the 2001-switch-out group in the first switch-out year, but the effects disappear next year.

According to Auffhammer and Kellogg (2011), NOx emissions in a region can affect ozone levels up to 1000 km downwind. Moreover, it is observed that the average county pollution yield from the off-road engines and vehicles exhibit an increasing trend over the period between 1990 and 2002 (see Figure 4), so that on-road emission levels of VOCs, NOx, and CO are being approached by the off-road levels, with the level ratios of 2.70, 1.59, and 1.59 for VOCs, NOx, and CO, respectively, in 2002. Therefore, off-road pollution potentially plays a role in determining local air quality. The current study examines if the fuel regulations also control the emissions from the off-road engines and vehicles.

However, no environmental gains from the off-road sources are found for the counties that adopted the RFG fuels in 1996. This is reflected by the statistical insignificance of the estimated treatment effects presented in Table Tab. 1.7 and the insignificance holds even when either emission densities or emissions per capita is used as the dependent variable.

Table Tab. 1.8 provides us with the treatment effects of the RVP and OXY on the off-road emissions. Similarly, significant pollution reductions still cannot be found for the different RVP-switch-in groups, no matter which temporal scope is specified and which measure of the dependent variable is used. Furthermore, the off-road CO emissions from the OXY

Table 1.7: RFG effects, off-road engines and vehicles

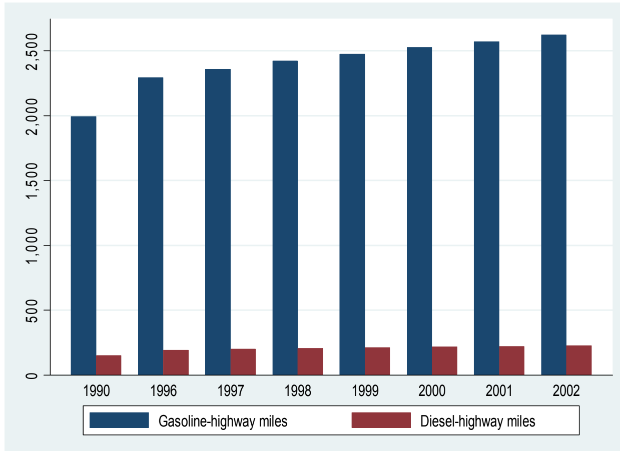
RFG	1996-switch-in		
	VOCs	NOx	CO
	Emission levels (tons)		
Trfgdafter	33.02	135.3	1751.3
	(218.3)	(687.8)	(2136.1)
	Emissions per capita (kgs)		
Trfgdafter	-6.500	0.719	-7.171
	(5.992)	(3.882)	(18.19)
	Emissions per square mile (tons)		
Trfgdafter	0.482	1.208	7.752
	(1.173)	(5.333)	(8.543)

Notes: 1. The numbers in parentheses are the standard errors. 2. *, **, and *** denote statistically significant at 10%, 5%, and 1%, respectively.

1996-switch-in regimes are not affected. Regarding the OXY switch-out groups, the separate policy effects show that the changes in CO levels between treatment and control groups are not significant once the OXY-regulated regions quit using cleaner oxygenated fuel, with an exception of the 2002-switch-out group (also see Table Tab. 1.8). However, the generalized regulation effects across different switch-out groups are all insignificant.

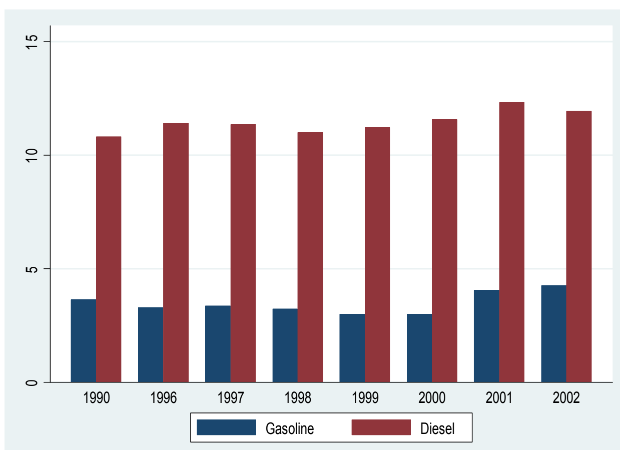
As a summary of all the findings above, it can be concluded that all three clean fuel regulations did effectively control the pollution emitted from the on-road vehicles but not off-road sources. The different policy effects in terms of reducing the on-road and off-road emissions result from the fact that gasoline is the major fuel to power on-road vehicles, while diesel is the major fuel consumed by off-road engines and vehicles. Figure 5 illustrates that the miles driven by gasoline-highway vehicles are dramatically higher (at least 11 times) than the miles driven by diesel-highway vehicles from 1990 to 2002. Meanwhile, within the off-road sector the consumption of gasoline is only about one third of the consumption of diesel, see Figure 6. Therefore, the regulations can have a greater influence on the emissions from on-road sources.

Figure 1.5: Vehicle miles driven by gasoline- and diesel-highway vehicles (10^9 miles)



Notes: 1. Gasoline-highway miles include miles traveled from passenger cars, light-duty trucks, heavy duty vehicles, and motorcycles. 2. Diesel-highway miles include miles traveled from passenger cars, light-duty trucks, and heavy duty vehicles. Source: US EPA, Inventory of U.S. greenhouse gas emissions and sinks: 1990-2002.

Figure 1.6: Gasoline and diesel consumption, off-road sources (10^9 gallons)



Source: US EPA, Inventory of U.S. greenhouse gas emissions and sinks: 1990-2011, Annexes.

Table Tab. 1.9 further shows that the diesel consumption by non-highway vehicles tends to increase over the sample period. The increase in diesel results mainly from more utilization of ships and boats, construction equipment, and locomotives.

1.6 Conclusion

The introduction of gasoline content regulations resulted in a dramatic reduction in vehicle-emitted pollution during the period 1990 to 2002, even though the number of vehicles and miles driven increased during that time. The current paper tries to isolate the effects of the regulations by using emission levels instead of ozone levels. All counties in the U.S. are first allocated into different treatments groups (the OXY-treated group, the RFG-treated group, and the RVP-treated group) and a control group depending on whether or not a county is regulated and what type of regulation is adopted if it is under-regulated. A difference-in-difference strategy is then carried out to identify the differential of the emission reductions between the regulated groups and the control group.

The empirical findings showed that, the pollution reductions were substantial with adopting the RFG, RVP, and OXY programs in 1996 to the severely polluted counties compared with the ones which adopted conventional gasoline. For the counties that adopted the RVP fuel later than 1996, the RVP-treatment effects can be observed to increase over time, though the estimated values are not statistically significant (except for the 2000-switch-in counties). Thus, this particular program might be more effective over the long-run. Further, once a county switched out of the OXY program, the CO-reduction effects induced by this program ceased.

Moreover, the current study illustrates that the off-road emissions of the related pollutants increased as time span expanded and were not well controlled by the clean fuel programs. This policy ineffectiveness may be explained by the fact that diesel is the major fuel used in the off-road sector. As a result, the emissions from this sector were less affected by the fuel content regulations.

In agreement with the point made by Auffhammer and Kellogg (2011), that the fuel refiners had choices to choose how to comply with the fuel content standards specified under the RFG and RVP regulations may have significant impacts on ozone levels. Moreover, the off-road emissions may also substantially influence the local air quality. Therefore, the increased and less affected pollution from the off-road sources could nullify the environmental benefits by adopting clean fuels. This may be an additional explanation for why local air quality did not improve though the clean RFG and RVP fuels were prescribed to some areas with severe pollution.

Table 1.8: RVP and OXY effects, off-road engines and vehicles

RVP	1996-switch-in	1998, 1999, and 2000-switch-in				
	1990-1996	1-year-in	2-year-in	3-year-in	4-year-in	5-year-in
	VOCs emission levels (tons)					
		Generalized effects				
Trvpdafter	-81.66	49.66	37.41	62.72	-49.04	-150.3
	(226.5)	(78.62)	(77.58)	(87.39)	(130.7)	(376.9)
		Separate effects				
TrvpdafterP1		-136.1	4.746	-206.7	-193.1	-150.3
		(184.6)	(187.8)	(185.8)	(184.2)	(376.9)
TrvpdafterP2		-87.01	5.690	-130.7	-11.87	
		(90.76)	(87.66)	(89.79)	(119.5)	
TrvpdafterP3		116.2	82.82	-14.02		
		(91.75)	(89.65)	(104.1)		

OXY	1996-switch-in	2000, 2001, and 2002-switch-out		
	1990-1996	1-year-out	2-year-out	3-year-out
	CO emission levels (tons)			
		Generalized effects		
Toxydafter	-505.0	-471.4	450.2	-858.7
	(1203.7)	(2769.0)	(4119.2)	(3552.4)
		Separate effects		
ToxydafterP1		-300.4	-579.8	-858.7
		(3569.4)	(3836.0)	(3552.4)
ToxydafterP2		94.69	2531.3***	
		(84.63)	(120.6)	
ToxydafterP3		-1233.5***		
		(109.6)		

Notes: 1. The numbers in parentheses are the standard errors. 2. *, **, and *** denote statistically significant at 10%, 5%, and 1%, respectively.

Table 1.9: Fuel consumption for non-highway vehicles by fuel type (10^3 gallons)

Vehicle Type	1990	2002	change
Aircraft			
Gasoline	374,216	280,643	-33%
Jet Fuel	18,280,137	18,499,519	1%
Ships and Boats			
Diesel	1,697,600	2,014,416	16%
Gasoline	1,300,400	1,081,157	-20%
Residual	2,060,708	2,404,778	14%
Construction Equipment			
Diesel	1,581,500	1,818,411	13%
Gasoline	318,200	532,998	40%
Agricultural Equipment			
Diesel	3,164,200	3,233,874	2%
Gasoline	812,800	831,828	2%
Locomotives			
Diesel	3,450,643	4,160,463	17%
Other			
Diesel	926,800	709,339	-31%
Gasoline	1,205,400	1,810,509	33%

2 Evaluating the Environmental Effects of the "Cash for Clunkers" Program

2.1 Introduction

Accelerated vehicle retirement programs have become popular among governments wanting to address air pollution and the adverse effects associated with vehicle usage. In the United States, the Consumer Assistance to Recycle and Save (CARS) Act was signed into law on June 24, 2009, establishing the Car Allowance Rebate System (CARS) program, commonly known as the "Cash for Clunkers" program, which went into operation on July 1, 2009, with a few vehicles transactions completed before July 27, 2009, when it was officially launched. The CARS program offered a \$3,500 or \$4,500 incentive to participants who retired their current vehicles and purchased a new vehicle, provided that certain requirements on fuel economy improvements and vehicle categories were satisfied.

The "Cash for Clunkers" program led to 676,984 final transactions (updated as of November 10, 2010), at a cost of \$2.85 billion, far above the initial cost budget of \$1 billion. The program was terminated on August 25, ahead of its original end date of November 1, 2009. The motivation for implementing this program was to stimulate economic growth and decrease unemployment by shifting vehicle purchases made by households, businesses, and governments from the future to the present. The program also aimed to accelerate the replacement of "dirty" gas guzzlers by new, cleaner, and high efficiency vehicles. In this paper, only the pollution-reduction effects are examined.

To evaluate the environmental effects of a vehicle scrappage program, three factors need to be determined: travel schedules, emission factors, and vehicle survival rates for both retired vehicles and their replacements. Two assumptions on the travel demand of retired and replacement vehicles are often adopted by the literature. First, some earlier studies assume that a retired vehicle is driven at the average of the vehicles of a particular type and vintage (for example, see Li et al., 2013). The average is often taken from Lu (2006)'s "Vehicle survivability and travel mileage schedules". However, this average is estimated at an aggregate level based only on vehicle age and vehicle type, so it could be significantly different from the travel schedules specific to the retired vehicle. This problem most likely occurred with the CARS vehicles because the trade-in vehicles required by the program were old and had low fuel efficiency and the current study shows that retired vehicles travel less than the fleet average.

Second, it is often assumed that the vehicle miles traveled (VMT) schedules for the retired and replacement vehicles are the same (for example, see Antweiler and Gulati (2011) and Sandler (2012)), because the same vehicle owner may not change their driving habit. However, assuming the same travel demand may be problematic. New vehicles in general provide better performance, more comfort and higher level of safety to their owners; in addition, the unit driving cost for these vehicles is lower due to their higher fuel efficiency. Thus, a new vehicle is likely to travel more than its paired retired vehicle in the trade-in year. The current study also illustrates that the annual VMTs on average declines with a vehicle's aging and fuel efficiency depreciation.

The current paper differs from most scrappage studies because its analytical framework is adopted from the urban economics literature. This literature has comprehensively examined how urban form, such as residential densities, along with household characteristics explain travel behavior (for example, see Bento et al. (2005) and Brownstone and Golob (2009)).

Based on the rich set of household and vehicle characteristics contained in the National Household Travel Survey (NHTS) 2009, the VMT schedules are first derived for the NHTS vehicles. Next, the NHTS vehicles are matched with the CARS vehicles to construct the VMT demand specific to the trade-in and replacement vehicles that participated in the CARS program.

Moreover, the endogeneity issue of fuel efficiency (or self-selection issue) is also addressed in the current paper in order to examine the relationship between fuel efficiency and vehicle travel demand. If a household expects to drive more, it is more likely for the household to choose a more efficient vehicle. As a result, the observed highly positive effects of fuel efficiency on VMTs may arise from the household's self-selection on vehicle choices. Because the CARS program created a big gap in in fuel economy between the trade-in and replacement vehicles, an empirical study could overestimate the travel demand for the new CARS vehicles and thus their pollution without taking into account the endogeneity issue.

The current study also differs from other scrappage studies because it takes into account "indirect" vehicle emissions, for example, diurnal exhaust, to evaluate the "Cash for Clunkers" program.[1] The "indirect" emissions bring additional emission gains to the CARS program as older retired vehicles tend to produce more "indirect" emissions compared to their newer replacement vehicles. Empirically, the current paper examines the environmental effects of the CARS program on the following pollutants: reactive organic gases (ROG, with a same class as EPA's volatile organic compounds (VOC)), total organic gases (TOG), nitrogen oxide (NOx), carbon monoxide (CO), carbon dioxide (CO2), sulfur oxide (SOx), particulate matter 10 micros or less in diameter (PM10), and particulate matter 2.5 microns or less in diameter (PM2.5).

Based on the "model-predicted" VMTs, this paper shows that for the participating Californian vehicles, the program resulted in reducing the emissions in ROG, CO, NOx, and PM2.5

[1] According to the EMFAC2011-LDV User's Guide, "diurnal exhaust" refers to the hydrocarbons emissions caused by fuel evaporation from a sitting vehicle throughout a day when ambient temperatures rise.

by 95%, 90%, 94%, and 7%, evaluated as $1.07, $2.99, $1.55, and $0.01 million, respectively, while CO2, SOx, and PM10 emissions increased by 20%, 16%, and 16%, evaluated as $82.43, $0.004, and $0.007 million, respectively.[2] Therefore, this paper concludes that the positive gains from the reduced emissions of ROG, CO, NOx, and PM2.5 were completely offset by the increased CO2 emissions, with a loss of approximately $76.82 million, at an aggregate level (or $1003.9 dollars per program vehicle).

The environmental effects of the program are also evaluated under the two standard scenarios. The first scenario assumes that the new vehicles will travel the same amount as their paired old vehicles, while the second scenario assumes that the new vehicles will travel at the fleet average. As argued earlier, the VMTs predicted by the regression model in this paper for the new vehicles should be greater than the fleet average, while the VMTs for the old vehicles should be smaller than the average. Thus, the changes in the net emission derived under the regression model and the changes derived under the first scenario are the lower and upper limits of the program effects, respectively. The net program effects under the best scenario are found to be positive, with a gain of $35 million or of $458 per vehicle. Regarding the middle case, the net effects are still negative as $60.23 million or $787.2 per vehicle.

This paper shows that VMTs are highly affected by vehicle type, age, and fuel efficiency etc. and replacement vehicles tend to be driven more than the paired retired vehicles. Therefore, the paper concludes that implementing the CARS program is more likely to result in negative environmental effects. The negative effects can be explained by the empirical finding that the emission rates for ROG, TOG, CO, and NOx play a more dominant role in determining a vehicle's emissions compared to VMTs and survival rates because the magnitudes of the emissions rates significantly increase with vintage. As a result, old vehicles are more likely to produce more emissions of the four pollutants listed above.

With respect to CO2, SOx, PM10, and PM2.5, VMTs are more dominant in determining a vehicle's pollution because CO2 and SOx emissions are closely correlated with fuel con-

[2] The model hereafter refers to the system of two equations (1) and (2).

sumption and fuel properties, and, in turn, fuel consumption is closely correlated with VMT. Therefore, the emission rates for CO2 and SOx do not differ dramatically across old and new vehicles. As a result, the new vehicles tend to emit more CO2 and SOx because they are driven more. Similarly, PM10 and PM2.5 are emitted mainly as a result of brake use and tire wear, so they are also highly related to how much a vehicle is driven.

Moreover, this paper also finds some evidence that some program participants would have traded in their current vehicle in order to purchase another vehicle without being offered the program incentive: 16,801 new vehicle purchasers out of 143,827 survey respondents, a weight of 11.68 percent, may have fallen into the category of adverse selection.

Furthermore, the program also changed the category selection of the vehicle purchased by the participants, and this change potentially determined the future pollution and fuel consumptions of the newly purchased vehicles. In order to be eligible for the CARS program, a transaction had to satisfy stringent and binding conditions for fuel-efficiency improvements. These conditions could have made program participants choose a vehicle with higher fuel economy than that of a vehicle chosen without being offered the $3,500 or $4,500 CARS incentive. The result would have been a significant trade-in bonus.

Of course, the binding requirements for improvements in fuel efficiency also applied to the vehicle owners in the case of adverse selection, and could potentially have caused these owners to choose smaller and more fuel-efficient vehicles. Choosing a vehicle with higher fuel efficiency could have reduced pollution for some pollutants, even under the existence of adverse selection. To some extent, this argument differs from traditional arguments concerning adverse selection because the literature tends to ignore the emissions effects of the vehicles susceptible to adverse selection.

The rest of this paper is organized as follows. Section 2 presents the background and descriptions of the Cash for Clunkers program. Section 3 presents the relevant literature and discusses the contribution of and the difference between our study and the previous literature. Section 4 describes our data, and then Section 5 provides our regression model and estimation results. Section 6 presents the methodology of the current study and the environmental effects of the CARS program, and then discusses the findings. Section 7 contains the conclusion of the paper.

2.2 Background of the “Cash for Clunkers” program

To be qualified as an eligible trade-in vehicle for the “Cash for Clunkers” program, a vehicle had to be under 25 years old and drivable and to have a fuel economy below 18 miles per gallon (mpg); in addition, the vehicle had to have a continuous insurance record, and the trade-in owner had to have owned the vehicle for at least one year.

However, a Category 3 vehicle (trucks, vans, or SUVs with vehicle weight rating between 8,500 to 10,000 lbs) had to be from a model year not later than model year 2001 and had no fuel economy requirements (for the classification of vehicle categories under the CARS program, see Table Tab. 2.1 below). The manufacturer's suggested retail price of a replacement vehicle could not be over $45,000, and the minimum fuel economy for passenger cars, Category 1 trucks, and Category 2 trucks was 22, 18, and 15 mpg, respectively.

Table Tab. 2.1 also presents the bonus scheme stipulated by the CARS program. The bonuses were conditional on the satisfaction of the eligibility criteria. Table Tab. 2.1 illustrates that the amount of a bonus depended on the category and fuel economy of the trade-in and replacement vehicle pair. For a trade-in vehicle that was a passenger car, Category 1 truck, or Category 2 truck, and a replacement vehicle that was a passenger car, if the fuel economy was improved by 4 to 9 miles per gallon, the trade-in credit was $3,500; and if the fuel economy was improved by at least 10 miles per gallon, the credit was $4,500. For a trade-in vehicle that was a passenger car, Category 1 truck, or Category 2 truck, and a replacement vehicle that was a Category 1 truck, if the fuel economy was improved by 2 to 4 miles per gallon, the trade-in credit was $3,500, and if the fuel economy was improved by at least 5

Table 2.1: Vehicle categories and incentive scheme under the CARS program

Old vehicle type	**Wheelbase**	**Old vehicle mpg**	**GVWR**[1]	**New vehicle type**	**New vehicle mpg**	**MPG improvement**	**Bonus**
Passenger Car							
	NA[2]	<=18 mpg	<=6,000 lbs	Passenger Car	>=22 mpg	4-9 mpg	3500
						>=10 mpg	4500
				Category 1 Truck	>=18 mpg	2-4 mpg	3500
						>=5 mpg	4500
Category 1 Truck							
Sport utility vehicles	NA[2]	<=18 mpg	<=8,500 lbs	Passenger Car	>=22 mpg	4-9 mpg	3500
Minivans						>=10 mpg	4500
Small and medium pickup trucks	<=115 inches			Category 1 Truck	>=18 mpg	2-4 mpg	3500
Small and medium passenger and cargo vans	<=124 inches					>=5 mpg	4500
Category 2 Truck							
Large pickup trucks	>115 inches	<=18 mpg	<=8,500 lbs	Passenger Car	>=22 mpg	4-9 mpg	3500
						>=10 mpg	4500
				Category 1 Truck	>=18 mpg	2-4 mpg	3500
Large vans	>124 inches					>=5 mpg	4500
				Category 2 Truck	>=15 mpg	1 mpg	3500
						>=2 mpg	4500
Category 3 Truck							
Trucks, vans, and SUVs	NA[2]	NA[3]	>8,500 lbs & <10,000 lbs	Category 2 Truck	>=15 mpg	NA[3]	3500
				Category 3 Truck	NA[3]	Smaller or similar in size	3500

Notes: 1. GVWR refers to gross vehicle weight rating. 2. Wheelbase requirements are not applicable. 3. No minimum fuel economy requirement is available for Category 3 trucks because their fuel economy was not rated.

miles per gallon, the credit was $4,500.

If a replacement vehicle was a Category 2 truck, its paired trade-in vehicle had to be a Category 2 or Category 3 truck, and the trade-in vehicle could not be a passenger car or a Category 1 truck. If the trade-in vehicle was a Category 2 truck, an improvement of fuel economy by 1 mile per gallon or at least 2 miles per gallon led to a $3,500 or $4,500 credit, respectively, while the trade-in credit was $3,500 if the trade-in vehicle was a Category 3 truck.

In the case of a new Category 3 truck, its paired traded-in vehicle had to be within the same category. For a transaction involving two Category 3 trucks, the trade-in credit was $3,500, provided that the new vehicle was smaller or similar in size. The National Highway Traffic Safety Administration (NHTSA) interpreted this requirement to mean that the new vehicle had to have a gross vehicle weight rating no greater than that of the old one.

Generally, passenger cars have a higher fuel economy than light-duty trucks; thus, a higher improvement in fuel economy was required to obtain the bonus if the replacement vehicle was a passenger car. It can also observe that the requirements for fuel improvement became less stringent as the replacement vehicles became larger in size, because larger vehicles on average have a lower fuel economy, and improving their fuel economy is mechanically difficult.

The CARS program was implemented in the hope of accelerating the replacement of gas guzzlers by vehicles with high fuel efficiency. Therefore, the program had to guarantee that the retired vehicles could not return to the road. In general, this requirement was achieved by requiring automobile dealers to operate the engine of a trade-in vehicle with a sodium silicate solution (liquid glass) until the engine was disabled. Finally, the old vehicles were crushed or shredded at a disposal facility.

2.3 Literature review

Understanding how much the retired vehicle and its replacement would be driven is a crucial question to determine the environmental effects of an accelerated vehicle retirement program. Dill (2004) demonstrates that the pollution reduction effects of such a program could vary dramatically based on the different assumptions on the VMTs of the vehicles participating in two California retirement programs.

A fixed VMT or the average by vehicle type and age from Lu (2006) is assumed by recent scrappage studies that are closely related to the current paper. Knittel (2009) evaluates the cost of reducing carbon dioxide under the "Cash for Clunkers" program. He simply assumes that all trade-in vehicles were driven by a fleet average, 12,000 miles annually, regardless of their characteristics such as vehicle type, age and fuel economy. New vehicles could be annually driven for either the same or more miles as the trade-in vehicles, depending on what values of the parameters on rebound effects are assumed. Knittel calculates that it costs at least $237, an expensive way, to reduce carbon emissions by one ton under the program. In addition, he shows that the carbon-reduction effect of the program can be negative when the Lu's (2006) average is adopted.

Li et al. (2013) examine the effects of "Cash for Clunkers" on new vehicle sales, employment, fuel consumption, and the environment. Using a difference-in-difference approach with Canada as the control group, these researchers find that a significant increase in vehicle sales occurs during the program, with a net sales increase of 0.25 million from June to December of 2009, and that the program creates 3,676 job-years during the same period. However, the increase in vehicle sales in the long run is estimated as 30,579 or zero because the program borrowes vehicle sales from the future. To evaluate the pollution effects of the program, Li et al. (2013) simply assume that the trade-in and new vehicles follow Lu (2006)'s average VMTs, determined by vehicle type and vintage. The program is found to reduce CO2 emissions by 8.58 to 28.28 million tons, implying that a cost of $91 to $301 to reduce a ton of

CO_2 emission.

Antweiler and Gulati (2011) evaluate BC SCRAP-IT®, British Columbia's accelerated vehicle retirement program. Their study is an improvement over earlier scrappage studies by providing more accurate estimation of VMTs and vehicle-specific emissions for the retired vehicles. Approximately 70% of their sample vehicles are inspected by British Columbia's Motor Vehicle Emissions Inspection and Maintenance Program (AirCare). The AirCare dataset includes odometer readings and emission test records for the retired vehicles. By using the vehicle's last two inspection results, Antweiler and Gulati (2011) construct better estimates on the vehicle's end-of-life annual VMTs and associated pollution. In addition, they assume that replacement vehicles have the same annual travel schedules as trade-in vehicles and find that a program vehicle on average saves 10.5 tonnes of CO_2, 70 kg of NO_x, 28 kg of HC, and 405 kg of CO, totally valued at C$859.

Sandler (2012) also improves the VMT estimation for the retirement vehicles participated in the California's Bay Area's vehicle buyback program. A refined control vehicle group is chosen to match with the retired vehicles based on vehicle identification number (VIN) and registered location, and then odometer readings are used to calculate the VMTs of the control group, which are served as the counterfactuals of the retired vehicles. Thus, his evaluation on the program does not adopt any standard assumptions on the scrapped vehicles in the literature. However, due to the lack of information on replacement vehicles, Sandler also assumes that the replacement vehicles are driven the same number of miles as the trade-in vehicles and concludes that both the depreciation of the vehicle fleet and adverse selection lead to a decline in the vehicle retirement program's cost-effectiveness over time.

The current study argues that assuming a fixed VMT or the average from Lu (2006) may not be appropriate when examining the CARS program. Given the program requirements, the old vehicles have to be gas guzzlers with a fuel economy lower than 18 mpg (except for the Category 3 trucks), while the replacement vehicles tend to have high fuel efficiency. For example, in order to obtain a $4500 bonus, an improvement of 10 mpg has to be achieved when a CARS transaction involves two passenger cars. Hence, the use of the vehicles participating in the CARS program could potentially deviate from the average.

Antweiler and Gulati (2011) and Sandler (2012) use more appropriate approaches to determine the VMT schedules for the retired vehicles during their end of life; however, the assumption that the retired and new vehicles travel the same amount may not be justified. First, the marginal cost of driving new vehicles decreases because of the improvement in fuel efficiency for the replacements. Second, vehicle owners tend to trade in vehicles not being used, and third, the new vehicles in general provide more comfort to drivers Knittel (2009). Lastly, a change in vehicle type could also occur following a CARS transaction, which would affect travel behavior.

From a broader literature, the VMT prediction for the CARS vehicles may also be informed by the studies which examine the relationship between vehicle fuel efficiency and VMTs, for example, studies which investigate the fuel efficiency rebound effect (for a review of the rebound effect literature, see Sorrell et al., 2009). Among these studies, the endogeneity of vehicle fuel efficiency needs to be controlled for in order to provide a more accurate VMT estimates. Small and Dender (2007) state that households have their expected travel demand and are likely to choose a vehicle with higher fuel efficiency than other households if they tend to drive a long distance regularly. Thus, a household's expected amount of driving can affect its vehicle choice and the observed high volume of travel associated with high fuel efficiency may be just a reflection of a household's vehicle selection. Therefore, accounting for the endogeneity would not over-estimate VMTs for the CARS replacement vehicles of high efficiency and the pollution yield by these vehicles.

Using instrumental variables for vehicle fuel efficiency is one way to address the endogeneity (e.g., see Liu (2009)). Jointly modeling fuel efficiency and VMT decisions is another way used to control for the endogeneity of fuel efficiency. In general, the jointly modeling can be implemented through either using simultaneous equation estimation technique (e.g., Greene et al. (1999) and Small and Dender (2007)) or jointly estimating the discrete choice of vehicle and the continuous choice of VMTs conditional on vehicle choice (e.g., Goldberg (1998), West (2004), Bhat and Sen (2006), and Bhat et al. (2009)).

Rather than using the typical VMT numbers assumed by the scrappage literature or vehicle odometer readings, the current paper refers to the efficiency&VMT literature to derive the travel demand for the CARS vehicles. Particularly, this paper follows Liu (2009) to use the price of gasoline when a household purchases its vehicle along with other variables as instruments to correct the potential endogeneity problem. As argued earlier, instrumenting the fuel efficiency is not the only way to reveal the relationship between the efficiency and VMTs, but adopting this approach can relax some assumptions imposed by some jointly modeling studies, such as a symmetric response to both gasoline prices and fuel efficiency or as a fixed total mileage budget for each household (for the related critiques, see West et al. (2014) and Liu et al. (2014)). The computation of the discrete-continuous model could also be intensive.

In addition, the rich information on residential densities, and household and vehicle characteristics contained in 2009 NHTS is also used by the study to predict the VMTs during a vehicle's lifetime. Density is used because it is the most frequently used in the urban economics literature as an indicator of urban sprawl because density can be consistently measured across space and time and is readily available (e.g., see Bento et al., 2005). Density is also a proxy for access to employment, shopping, and other travel destinations, so it can potentially influence VMT Brownstone and Golob (2009).

A recent study by West et al. (2014) adopts regression discontinuity design to examine the change in household's driving behavior for one year after the CARS transaction. They argue that the CARS program creates a credibly exogenous "policy-induced improvement" in fuel efficiency. They collect the data on new car buyer in Texas during the CARS program in 2009, provided that these buyers' retired "clunkers" are either barely eligible and barely ineligible for the CARS subsidy. They find that 4 to 6 percent more fuel efficient vehicles are purchased by the barely eligible new car buyers compared to the barely ineligible new car buyers, however, the former does not drive more miles than the latter. Therefore, they conclude that the rebound effect tends to be insignificant. The finding from West et al. (2013) is consistent with ours in the sense that the current study also finds an economically small effect of fuel efficiency on VMTs.[3]

2.4 Data

The 2009 National Household Travel Survey (NHTS) has rich information for investigating household travel behavior. A system of regression equations (described in the next section) is estimated based on the urban form indicator, household characteristics, and vehicle attributes from the 2009 NHTS. Once the coefficient estimates for the regression system are obtained, the VMT values can be predicted for each NHTS vehicle during its residual lifetime.

To determine the VMT for the CARS vehicles, a vehicle cohort is first defined by vehicle type and age, and then the mean fuel economy for each CARS vehicle cohort is calculated based on the transaction details contained in the Car Allowance Rebate System dataset. Next, the NHTS vehicles are matched with the CARS vehicles according to vehicle cohort and the calculated mean fuel economy. The VMT schedules of the each CARS vehicle cohort is then derived from the VMT of the matched NHTS vehicles with a same cohort.

Now, the emissions for the CARS vehicles can be estimated by combining the VMT schedules with the emission factors retrieved from the EMission FACtors (EMFAC) 2011 model, provided the counts of each CARS vehicle cohort are determined. The California sub-datasets from the 2009 NHTS and the CARS datasets are used to evaluate the environmental effects of the CARS program because the EMFAC2011 is modeled to predict the emissions emitted by the vehicles operated in California.

[3] To see this, compare Figure 3(b) on P.24 to Figure 5(b) on P.26.

CARS data

The CARS data contains the details for 676,984 vehicle transactions (updated as of November 10, 2010). In California, 76,514 vehicles participated in the program, accounting for around 11.30 percent of all CARS transactions. The data provide information, such as vehicle year, make, model, fuel economy, and vehicle fuel economy, for both trade-in vehicles and newly purchased vehicles. Based on this information, the input errors on vehicle category for the participating vehicles are corrected according to the CARS vehicle eligibility guide.[4]

Table Tab. 2.2 shows that, in California, the counts within each vehicle category dramatically changed with the implementation the CARS program. The counts of Passenger cars rose from 14,734 to 49,564, while, in contrast, the counts of Category 1, 2, and 3 all dropped. The category shares may provide a better view of the count changes. Specifically, the share of Passenger cars rose from 19.26 to 64.78 percent. This increase corresponds to a dramatic decrease in the share of Category 1 trucks from 67.66 to 31.21 percent, a moderate decrease in the share of Category 2 trucks from 12.53 to 3.85 percent, and a slight decrease in the share of Category 3 trucks from 0.55 to 0.17 percent. Table Tab. 2.2 also presents how the counts within each vehicle type changed according to vehicle category. The counts of Vans within Category 1 trucks dropped the most from 18,568 to 1,748, corresponding to a share drop of around 20 percent.

Moreover, a significant improvement in fuel economy can also be observed in Table Tab. 2.2. The highest increase of 11.79 mpg was achieved by Passenger cars due to the CARS program's more stringent requirements on fuel improvement, while the smallest improvement in fuel economy occurred in Category 2 trucks, with only an increase of approximately 2 mpg.

[4]The guide is available at `http://www.fueleconomy.gov/feg/CarsSearchIntro.shtml`.

Table 2.2: A brief view of vehicles participating in the CARS program

Category[1]	Type	Count		Percentage		Fuel economy	
		old	new	old	new	old	new
Passenger cars	Car	14,734	49,564	19.26	64.78	17.52	29.31
Category 1 trucks	Van	18,568	1,748	24.27	2.28	17.10	19.83
	SUV	28,563	17,744	37.33	23.19	15.25	22.30
	Pickup truck	4,435	4,174	5.80	5.46	16.62	20.29
	NA[2]	203	211	0.27	0.28	14.31	23
Aggregate		51,769	23,877	67.66	31.21		
Category 2 trucks	Van	1,165	21	1.52	0.03	13.22	15.52
	Pickup truck	8,411	2,922	10.99	3.82	14.35	16.37
	NA[2]	14	2	0.02	0.00		23
Aggregate		9,590	2,945	12.53	3.85		
Category 3 trucks	NA[2]	421	128	0.55	0.17		23
Total		76,514	76,514				

Note: 1. Vehicle category is defined by the CARS program, see Table Tab. 2.1. 2. There is not enough information to determine the vehicle types.

NHTS 2009

The NHTS 2009, which is conducted by the U.S. Department of Transportation, is the primary dataset used in the study. This dataset contains the household-level data on travel behavior from March 17, 2008 through May 7, 2009, and has 309,163 vehicles. As explained earlier, VMT, household residential densities, and household vehicle choices are key factors of interest in the current study. Table Tab. 2.3 presents the summary statistics for the relevant variables according to housing densities. This table reveals that both annual VMT and vehicle fuel economy exhibit a reverse relationship with respect to residential density. In addition, the households residing in the less dense areas tend to have higher annual family income and to own newer vehicles.

Moreover, gasoline prices are also a key factor to determine household VMT. Hence, more details on this variables need to be presented here.[5] The 2009 NHTS does not collect fuel prices via fuel purchase diaries. However, a fuel price is assigned to each NHTS sample

[5]Please refer to the documentation files "Methodologies for Estimating Fuel Consumption Using the 2009 National Household Travel Survey" and "Weekly Gasoline Prices, 2009 NHTS".

Table 2.3: Variable summary by residential density (N=277,194)

Housing units per square mile in Census block group	0-99	100-499	500-999	1K-2K	2K-4K	4K-10K	10K-25K	>25K
Best estimate of annual miles (in 1000 miles)	11.95	11.66	11.31	10.90	10.62	10.46	10.27	10.07
EIA derived miles per gallon	19.57	20.20	20.46	20.53	20.73	21.35	21.99	21.68
Vehicle age	8.67	7.83	7.68	7.88	8.27	8.40	8.42	7.40
Average household income (in 1000 dollars)	68.25	81.23	85.29	81.58	75.77	72.54	78.09	92.93

Source: calculated from the 2009 NHTS.

vhicle according to the vehicle's engine type and fuel type. Regarding gasoline, its type is first classifed by formulation (conventional, oxygenated, and reformulated gasoline) and further classified by grade (regular, midegrade and premium gasoline) within each type of gasoline formulation.

Gasoline prices used in the 2009 NHTS are retail prices and obtained from the Energy Information Administration (EIA) survey Form EIA-878 "Motor Gasoline Price Survey". More specifically, the retail prices are collected from a frame of approximately 115,000 retail gasoline outlets. Based on each outlet's zip code, individual outlets are mapped to counties. In addition, the gasoline prices are also monthly average prices with sample weights constructed by sales volume, surrogated by the sampled outlet's number of pumps. Lastly, the gasoline prices for a given NHTS household are determined by the Petroleum Administration for Defense Districts (PADD) designation to which this household belongs.

EMFAC 2011

The EMFAC model, developed by the California Air Resources Board (CARB), is used as an official tool to estimate emission rates and emission inventories from on-road motor vehicles in California. This information helps the CARB to design air-quality-related regulations and plans and to meet the Federal Highway Administration's transportation planning requirements.

The on-road emission rates were retrieved from a web-based data access tool, the EMFAC2011 Emissions Database (updated January, 2013),[6] which provides the emission rates at the Californian region levels and at the state level, the calendar year of interest, season, vehicle category, fuel type, vehicle model year, and driving speed. More specifically, the emission rates used in the current paper are for the annual state-wide average at a combined driving speed. Moreover, gasoline as fuel type is chosen because not enough information is available to determine the fuel type for the vehicles that participated in the CARS program.

The vehicle classes defined by the EMFAC2011 are slightly different from those defined by the CARS program (for more details on vehicle classification in the EMFAC2011, see Table Tab. 2.4). Thus, it is necessary to determine how the emissions rates modeled in the EMFAC2011 can be applied to the vehicles that participated in the CARS program. The Passenger Cars in the EMFAC2011 match Passenger Cars in the CARS program. The emissions rates for Light-Duty trucks of class 3 in the EMFAC2011 are applied to the Category 1 and Category 2 trucks because the average weights of Light-Duty trucks, including vans, sport utility vehicles (SUVs), and pickup trucks, with model years from 1975 to 2010, fall into the range of 3,751 to 5,750 lbs except in 1986 and 1987 (see Table Tab. 2.5). Finally, the emission rates for Light-Heavy-Duty trucks of class 5 apply to Category 3 trucks in the CARS program because they fall into the same vehicle weight range.

Table 2.4: Vehicle classes modeled in the EMFAC2011

Vehicle Class	Fuel Type	Code	Description	Weight Class (lbs)	Abbr.
1	All*	PC	Passenger Cars	All	LDA
2	All*	T1	Light-Duty Trucks	0-3,750	LDT1
3	Gas, Diesel	T2	Light-Duty Trucks	3,751-5,750	LDT2
4	Gas, Diesel	T3	Medium-Duty Trucks	5,751-8,500	MDV
5	Gas, Diesel	T4	Light-Heavy-Duty Trucks	8,501-10,000	LHD1

Note: * includes gas, diesel, and electric. Source: CARB, EMFAC2011-LDV User's Guide, September 19, 2011.

The pollutants modeled by the EMFAC2011 include ROG (the same class as EPA's volatile

[6]The database is available at `http://www.arb.ca.gov/emfac/`.

Table 2.5: Vehicle weight for 1975 to 2010 for Light-Duty Trucks

Model Year	1975	1976	1977	1978	1979	1980	1981	1982	1983
Weight (lbs)	4,072	4,155	4,135	4,151	4,252	3,869	3,806	3,806	3,763
Model Year	1984	1985	1986	1987	1988	1989	1990	1991	1992
Weight (lbs)	3,782	3,795	3,738	3,713	3,841	3,921	4,005	3,948	4,056
Model Year	1993	1994	1995	1996	1997	1998	1999	2000	2001
Weight (lbs)	4,073	4,125	4,184	4,225	4,344	4,283	4,412	4,375	4,463
Model Year	2002	2003	2004	2005	2006	2007	2008	2009	2010
Weight (lbs)	4,546	4,586	4,710	4,668	4,665	4,752	4,707	4,605	4,738

Source: EPA, Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2010.

organic compounds), TOG, CO, NOx, CO2, PM10, PM2.5, and SOx. The pollution reduction effects on all these pollutants are addressed in this study. Based on a vehicle's normal daily activities including starting, idling, running, or just sitting outside in the sun, the EMFAC2011 further classifies the emissions from a vehicle as the following types: running exhaust, idle exhaust, starting exhaust, diurnal emission, resting loss, hot soak, running losses, tire wear, and brake wear (see the definitions in Glossary of Terms). Correspondingly, the emissions of each pollutant are estimated as the sum of the different types of emissions of this pollutant.

2.5 Model and regression results

Following Liu (2009), a structural model below is used to estimate the travel demand for the CARS vehicles:

$$VMT_{ij} = a_0 + a_1 MPG_j + a_2 Gcost + X_i b_1 + V_j b_2 + \epsilon_i \tag{2.1}$$

$$MPG_j = F(X_i, V_j, Z_j) + \eta_j \quad (2.2)$$

where VMT_{ij} refers to annual vehicle miles traveled for vehicle j from household i. MPG_j is the fuel efficiency, miles per gallon and $Gcost$ is gasoline price. X_i is a vector of exogenous household characteristics such as household income levels, the number of household members, the number of primary drivers, the number of workers, and three household life cycle classification dummies. The first dummy is equal to 1 if the adults in a household have at least one child, the second dummy is equal to 1 if adults in a household have children, and the last dummy is equal to 1 if adults in a household have no children. [7] X_i also includes race dummies for the household survey respondents.

Following Brownstone and Golob (2009), housing density, measured by housing units per square mile at a block level, is also included in X_i as an explanatory variable. They argue that residential density can be regarded as a proxy for access to employment and other destinations and that, in general, households located in a less dense area might need to drive more distance to work places and other places like shopping malls. In addition, three dummies indicating whether or not a housing unit is owned or rented, heavy rail status, and whether or not a household is located in an urbanized area are all taken into account to explain vehicle usage.[8] ϵ_i is the unobserved household characteristics.

Vehicle attributes V_j includes three individual vehicle-type dummies: Vans, SUVs, and Pickup trucks (Automobiles are omitted). Vehicle age, age square, and age cubic terms

[7] The NHTS 2009 classifies the life cycle as follows: one adult with no children; two or more adults with no children; one adult with the youngest child aged 0 to 5; one adult with the youngest child aged 6 to 15; one adult with the youngest child aged 16 to 21; two or more adults with the youngest child aged 0 to 5; two or more adults with the youngest child aged 6 to 15; two or more adults with the youngest child aged 16 to 21; one adult, retired, with no children; and two or more adults, retired, with no children. These categories are compressed into the three categories used in the regression equation.

[8] The current study does not account for the vehicle use substitution effect as the chapter 3 does because the CARS dataset does not collect most of the household characteristics such as vehicle ownership.

are also controlled for in equation (1).[9] As argued earlier, a high MPG leads to a low marginal driving cost, and thus high volume of travel. Meanwhile, a household expecting to drive long road trips frequently may tend to choose a vehicle with high MPG. Hence, the joint decision of VMT and vehicle fuel efficiency causes the endogeneity of the explanatory variable MPG_j in equation (1).

To correct the potential endogeneity, Z_j is introduced into equation (2) as a vector of instruments of the variable MPG_j. To be valid instruments, Z_j should take effects on a household's vehicle choice, but not on the utilization of its vehicle. Equivalently, the instrumental variables affect MPG_j, but are independent of η_j, which is the unobserved vehicle characteristics is assumed by Liu (2009) to have the generalized extreme value distribution.

Again, following Liu (2009), the gasoline price when a household purchased vehicle j, effective CAFE standard when the household purchased vehicle j, and 30 vehicle brand dummies are used as instruments to control for the potential endogeneity.[10][11] Due to the data availability, state annual pre-tax gasoline price was used in the current study and the price is adjusted by price deflator with 2009 as the base year.Liu argues that a prevailing low gasoline price may cause a household to purchase a vehicle of low fuel efficiency, vice versa; however, the future utilization of the vehicle is more likely to be affected by the future fuel prices but not the price at purchase. The stringency of the effective CAFE standard can affect the average fuel efficiency of vehicle market, and thus, a household's vehicle choice, but it may not affect the household's travel demand after purchase. The decision on vehicle brand could reflect a household's preference. A household is likely to purchase a Japan-made car if the household

[9] Age square and age cubic terms are included following Lu (2006).

[10] Previous gasoline price may be more important than price at purchase in terms of determining a household's vehicle MPG choice. However, the period having "previous" gasoline price can not be too long ahead of the period in which a houshold purchases a vehicle because too early information may not affect a household's current behavior. If the interval between these two periods are not long, the gasoline price at purchase could be closely related to the "previous" price.

[11] The vehicle brands with the 30 highest weights in the 2009 NHTS are chosen as brand dummies. They are Acura, BMW, Buick, Cadillac, Chevrolet, Chrysler, Dodge, Ford, GMC, Honda, Hyundai, Infiniti, Isuzu, Jeep, Kia, Lexus, Lincoln, Mazda, Mercedes-Benz, Mercury, Mitsubishi, Nissan, Oldsmobile, Plymouth, Pontiac, Saturn, Subaru, Toyota, Volkswagen, and Volvo.

has more concern of reliability, while it may choose a German-made car if the household has more consideration on safety. On average, the former vehicle is more efficient than the latter. However, the usage of a vehicle may not depend on its brand.

The structural model presented above is chosen because it follows the traditional framework used in the urban economics literature to investigate vehicle travel behavior. In addition, Brownstone and Golob (2009) and Liu (2009) use the same dataset of the NHTS, but with the survey year of 2001, to investigate vehicle travel demand. More importantly, the specification above addresses the issue of fuel efficiency endogeneity and the chosen instrumental variables are tested by Liu (2009) as valid instruments. This specification is not the only way to estimate the VMTs, but it tries to employ all available information in the 2009 NHTS to provide an accurate estimation of VMTs. Table 6 provides the summary statistics for the variables associated with the model, which are calculated from the 2009 NHTS.

The model is estimated by using both the instrumental variables (IV) method and ordinary least squares (OLS) method. Column (1) of Table 7 below presents the IV estimates for the structural model. The column shows that 1 MPG improvement in the efficiency results in an increase in VMTs by 33.7 miles, annually. It also shows that the gasoline price negatively affects VMTs and 1 dollar increase in the price reduces annual VMTs by 506 miles. Thus, it may conclude that a household is more sensitive to the change in fuel price than to the change in fuel efficiency because the former is more noticeable. Households with higher income levels tend to drive more and an increase in income level by 10,000 dollars would lead to an increase in annual VMTs by only 53.6 miles. In addition, both household size and the number of workers take a positive effect on driving. An additional household member or worker leads to VMT increase by 351 or 652 miles.

The IV regression results also show that VMTs are negatively associated with the count of a vehicle's primary driver. A household's life cycle classification can also determine its travel. Compared to retired adults living with no children, adults living with children drive 2,058 miles more, while unretired adults living with no children drive 1,666 miles more. A vehicle owned by Asian is driven 696 miles less compared to the omitted group, but it is driven 572 miles or 955 miles more if the vehicle is owned by American Indian (or Alaskan Native) or Multiracial household.[12] As expected, a household locating in a more dense area is likely to have a lower travel demand: VMT would decrease by 101 miles if the household lived in area with 1000 more housing units per square mile. Home locates in a MSA with rail or in an urbanized area will reduce household travel by 241 or 982 miles.

Meanwhile, column (1) of Table 7 also demonstrates that vehicle type significantly affects a vehicle's usage. After controlling for other factors including fuel economy, Vans and SUVs are found to be driven 344 and 191 miles more than Pickup Trucks, respectively, while Automobiles are driven 563 miles less annually. Column (1) also illustrates that vehicle age affects VMTs. Vehicle age can reflect a vehicle's performance, as an older vehicle tends to have a worse performance and may be less safe, and thus is driven less miles than a newer vehicle.

Furthermore, the estimation results from OLS method are also presented in column (3) of Table 7 in order to compare them with those from IV method. Most coefficient estimates from the two different estimation methods have same sign and statistical significance and similar magnitude. However, the effect of fuel efficiency on VMTs is found to be nearly 19 times bigger effects under OLS method than that under IV method, approximately. Thus, correcting the potential endogeneity problem can present a more reliable relationship between fuel efficiency and VMTs.

2.6 Analysis of the environmental effects of the CARS

To evaluate the effects of the CARS program, the counterfactual emissions that the trade-in vehicles would have produced in their residual lives need to be determined, had they not been crushed or shredded. The amount of counterfactual emissions, in turn, depends on how

[12] The race for the omitted group is other specity not listed in the 2009 NHTS.

long the residual lifetime of a trade-in vehicle would have been, how many miles it would been driven annually, and how much pollution would have been produced for each mile that the vehicle traveled. In addition, vehicle survival rates also play a role in determining the amount of emissions because these rates measure the probability that a vehicle is still in operation during its residual life.

2.6.1 The VMT schedules for the trade-in and replacement vehicles

Mathematically, the pollution forgone from a trade-in vehicle i can be expressed as

$$\sum_{t^i}^{T^i} e(v^i,\, t^i) \cdot s(v^i,\, t^i) \cdot M(v^i,\, t^i), \tag{2.3}$$

where e, s, and M are the emission rates, vehicle survival rates, and annual VMTs for vehicle i, respectively. The notation implies that these three factors are time variant and dependent on vehicle type v^i and vintage t^i.[13] More specifically, the emission rates e are retrieved from the EMFAC 2011; and s is the vehicle survival probability conditional on a vehicle's survival until the age of $t-1$, and calculated from the estimated survival rates from Lu (2006).[14] Lastly, T^i refers to the lifetime of vehicle i. Following Lu (2006), the lifetime is assumed to be 25 years for Automobiles and 36 years for Vans, SUVs, and pickup Trucks.

The CARS program classifies vehicles into Passenger Cars, Category 1 Trucks, Category 2 Trucks, and Category 3 Trucks. In order to derive the annual VMTs, the CARS vehicle types need to be reclassified as Automobiles, Vans, SUVs, and pickup Trucks in order to match them with the types defined by the 2009 NHTS.[15] However, the Category 3 Trucks, which include large Trucks, Vans, and SUVs, are not reclassified, because of the lack of information

[13] The CARS program was implemented in 2009, so the vehicle age is calculated as 2010 minus the vehicle model year. In addition, the replacement vehicles with model years 2009 and 2010 were new in 2010, so they both are assumed to be age 1.

[14] Independence of hazard rates across years is assumed, and then the conditional survival rate of a vehicle, s_t^C, at time t equals s_t^U / s_{t-1}^U, provided that it has survived until $t-1$, where s_t^U and s_{t-1}^U are the unconditional survival rates at time t and $t-1$, respectively.

[15] The reclassification is performed based on vehicle make, model, and model year.

for doing so. Based on the arguments made above, v^i refers to one of the following vehicle types: Automobiles, Vans, SUVs, pickup Trucks, and Category 3 Trucks.

So far, the question of how to construct the VMT schedules for the trade-in vehicles has not been addressed. The procedure for answering this question begins by using the regression specification and coefficient estimates from Section sec. 2.5 to predict the annual miles driven by the NHTS vehicles . Next, the NHTS vehicles are matched with the CARS vehicles by using specific criteria, and the VMT schedules are then constructed for the latter. The details of the procedure are presented below.

For Automobiles, Vans, SUVs, and pickup Trucks, the miles currently driven by the NHTS vehicles in 2009 are determined as the predicted values of the dependent variable, VMT, in the regression equation (1). The future VMTs by these NHTS vehicles are estimated by combining the future values of the explanatory variables with the corresponding coefficient estimates from the regression equation (1). In the current study, it is assumed that variables related to the household characteristics are constant over time because the NHTS is not a time-series dataset, and the future values of these variables are not available.

The household life cycle and race variables are not likely to change within a short period; thus, they might not significantly affect the prediction of VMT; however, other household variables can affect the VMT prediction. For example, household income tends to increase over time, and thus to be positively related to VMT. Therefore, holding the household income constant may cause the future VMTs to be underestimated.

Moreover, the empirical findings in this study show that vehicle fuel efficiency has significant effects on VMTs, so understanding how fuel efficiency changes with aging is necessary. The mean MPG of the NHTS vehicles is first calculated according to vehicle type and age, and then the differences in the mean MPG of the same vehicle type between age t and $t-1$ are calculated. Next, a regression is run between the differences and a constant term by vehicle type, and the annual depreciation rates of the MPG are estimated as 1.07%, 1.14%, 1.47%, and 0.472% for Automobiles, Vans, SUVs, and pickup Trucks, respectively. As a result, the future MPG and thus the VMTs for the NHTS vehicles of these four types can be derived.

Based on the empirical results obtained by this study, household characteristics were found to significantly affect VMTs. Ideally, the CARS vehicles could be better matched with the NHTS vehicles in terms of VMT prediction if the household characteristics for the CARS participants were also known to us. However, the CARS program did not perform a survey to collect such information. Therefore, the matching process has to be based only on vehicle attributes as following: first, the mean fuel economy of the CARS trade-in vehicles is also calculated by cohorts defined by vehicle type and vintage, and then a range that contains the 2.5% upper and 2.5% lower limits of the mean fuel economy is determined.[16] However, the upper limit is not allowed to exceed 18 miles per gallon, the limit for a trade-in vehicle to be eligible for the CARS program. Next, the NHTS vehicles that not only match the vehicle type and age of the CARS vehicles but also fall into the fuel economy ranges determined by the CARS vehicles of the same type and age are kept. The VMTs of the remaining NHTS vehicles are averaged by vehicle type and age, and the averages are used as the predicted VMTs of the CARS trade-in vehicles.

The CARS program does not provide any information on fuel economy for Category 3 Trucks. Moreover, if a Category 3 Truck is a Van, SUV, or Truck cannot be determined. Therefore, a different approach must be used to determine the VMTs of Category 3 Trucks. As Category 3 Trucks are large Vans, SUVs, or Trucks, for simplicity the NHTS vehicles classified as Vans, SUVs, or Trucks are collapsed into one category, and the mean miles by year from the collapsed category are calculated as the VMT schedules for the CARS Category 3 Trucks. Now, all elements necessary to determine the forgone pollution from a trade-in vehicle i are available to us.

For a replacement vehicle j, the emissions produced by this vehicle during the residual life of its corresponding trade-in vehicle i, $(T^i - t^i)$, need to be estimated. However, the temporal

[16]The trade-in vehicles have 109 cohorts.

interval during which the accumulated pollution from the replacement vehicle j is calculated is based on $(T^i - t^i)$ but is not simply equal to $(T^i - t^i)$. Following Knittel (2009), the interval denoted as D^j is calculated as $D^j = \sum_{t^i}^{T^i} s_t^C$, where s_t^C is conditional survival rate of vehicle i.[17] Given the average age of the CARS retired vehicles is 15.7 years old, the expected number of years a CARS vehicle would be driven on road is calculated as 2.78 or 7.51 years depending on whether the trade-in vehicle is a car or a light duty truck, with an average of 6.60 years.[18]

Moreover, when determining the travel demands for the replacement vehicles, the interval D^j, together with vehicle type and vehicle age, is used to define the cohort to which the vehicle j belongs.[19] An additional dimension is introduced to estimate the VMTs of the replacement vehicles in order to help produce more accurate estimates of the VMTs and, thus, also of the emissions. Now, the emissions produced by the new vehicle j can be expressed as[20]

$$\sum_{t^j}^{D^j+t^j} e(v^j, t^j) \cdot s(v^j, t^j) \cdot M(v^j, t^j, D^j). \tag{2.4}$$

Similarly, the mean fuel efficiency of each of the new CARS vehicle cohorts defined as above is calculated, and then a MPG range is determined by using the 2.5% upper and lower limits of the mean MPG. Again, the NHTS vehicles are matched to the CARS according to vehicle type, age, and the MPG range. Finally, the VMT schedules of the CARS vehicles are calculated as the averages of the annual miles driven by the matched NHTS vehicles of

[17] For the notation, see footnote 10.

[18] For the vehicles that are more likely to be traded in even in the absence of the CARS program, they tend to have shorter lifetimes compared to those not expected to be traded in, which could lead to an overestimate of the VMTs for the retired vehicles.

[19] The replacements are classified into 498 cohorts. The average age of the replacements can be obtained as 1.02 years old

[20] It is possible that D^j is longer than the residual lifetime of a replacement vehicle j, $\left(T^j - t^j\right)$. Under this case, D^j should be replaced by $\left(T^j - t^j\right)$. Regarding the CARS trade-in vehicles, the youngest light duty truck is 3 years old, and then expected residual lifetime for these vehicles are estimated as 13.16 years.

On the other side, the shortest residual lifetime for a new CARS car is 22 years (note: some replacements have model year of 2007), which is still longer than 13.16 years, i.e, the longest residual interval for the trade-in vehicles. Therefore, D^j calculated by the method presented in the paper can be safely used as the interval to estimate the pollution from the replacement vehicles.

same cohort. The procedures discussed above apply only to Automobiles, Vans, SUVs, and pickup Trucks, while the approach used to predict the VMTs for the trade-in Category 3 Trucks applies to the new vehicles of same category. Again, the emission rates and vehicle survival rates for the replacements can be obtained from the EMFAC 2011 and Lu (2006), respectively.

Some additional points need to be addressed. First, the vehicle matching process is based on the prescribed fuel efficiency range, and also same vehicle type and vintage, but not household characteristics, because the CARS database does not collect information on these characteristics. Therefore, the changes in household characteristics could ocurr following the matching process proposed in this paper. For example, if an unaccounted increase in income across the matched NHTS households occurred, the current study could overestimate the VMTs for the replacement vehicles and their pollution. However, the unaccounted increase in income may not be dramatically high if low-income households are more likely to purse a fuel efficient but not a luxury and low fuel efficient vehicle. Given the data availability, this may be the best possible way to predict VMT for the new CARS vehicles.

Second, the structural model (1) is not used to predict the VMTs when a vehicle arrives at age 25 or older, regardless of which type it belongs to; instead, the 24-year VMTs are used when a vehicle's age exceeds 24, because the age range of the NHTS vehicles lies between 1 and 24; moreover, the model predicts that VMTs over 24 years old will tend to increase with age. This prediction contradicts the common observation that vehicles on average are driven less as they age. Using the 24-year VMT to predict a vehicle's future VMT could result in overestimating the VMTs, but may not significantly affect the estimation of the vehicle pollution because the magnitudes of both the VMTs and the vehicle survival rates are likely to be small when a vehicle's age is over 24.

Third, no information is available for identifying their types for some Category 2 Trucks and Category 3 Trucks. The differences between their individual fuel efficiency and the mean fuel efficiency determined by vehicle type and age are calculated. Next, the squares of the differences are taken and summed across vehicle age according to vehicle type. The smallest magnitude in a sum of square terms would indicate the closeness between the fuel efficiency of vehicles of an unknown type and those of a known vehicle type.

More specifically, the fuel efficiency is found to be closest to that of a pickup Truck for the trade-in vehicles and to that of a SUV for the new vehicles. Therefore, the vehicles of unknown types are identified as pickup Trucks if they are trade-in vehicles or SUVs if they are replacement vehicles, and their VMTs are calculated by using the method described above.

Figure 1 shows the expected VMT schedules by vehicle types for the trade-in vehicles of age 16 and replacement vehicles of age 1 and also with expected residual lifetime of 6.60 years.[21] [22] This figure shows that the miles driven by the vehicles of all types tend to decrease over time. The VMT trends across different vehicle types are also similar because the VMTs are all adjusted by vehicle survival rate, which is dramatically decreasing with vehicle's aging. Moreover, the new CARS vehicles have much higher VMTs compared to the trade-in vehicles at any given future year. The VMT differences can be explained by the big gap in vehicle age between the retired and replacement vehicles. In addition, the new vehicles have achieved significant improvements in fuel efficiency. Vehicle age and fuel efficiency are shown to have significant effects on VMTs (see the regression results in Table 7).

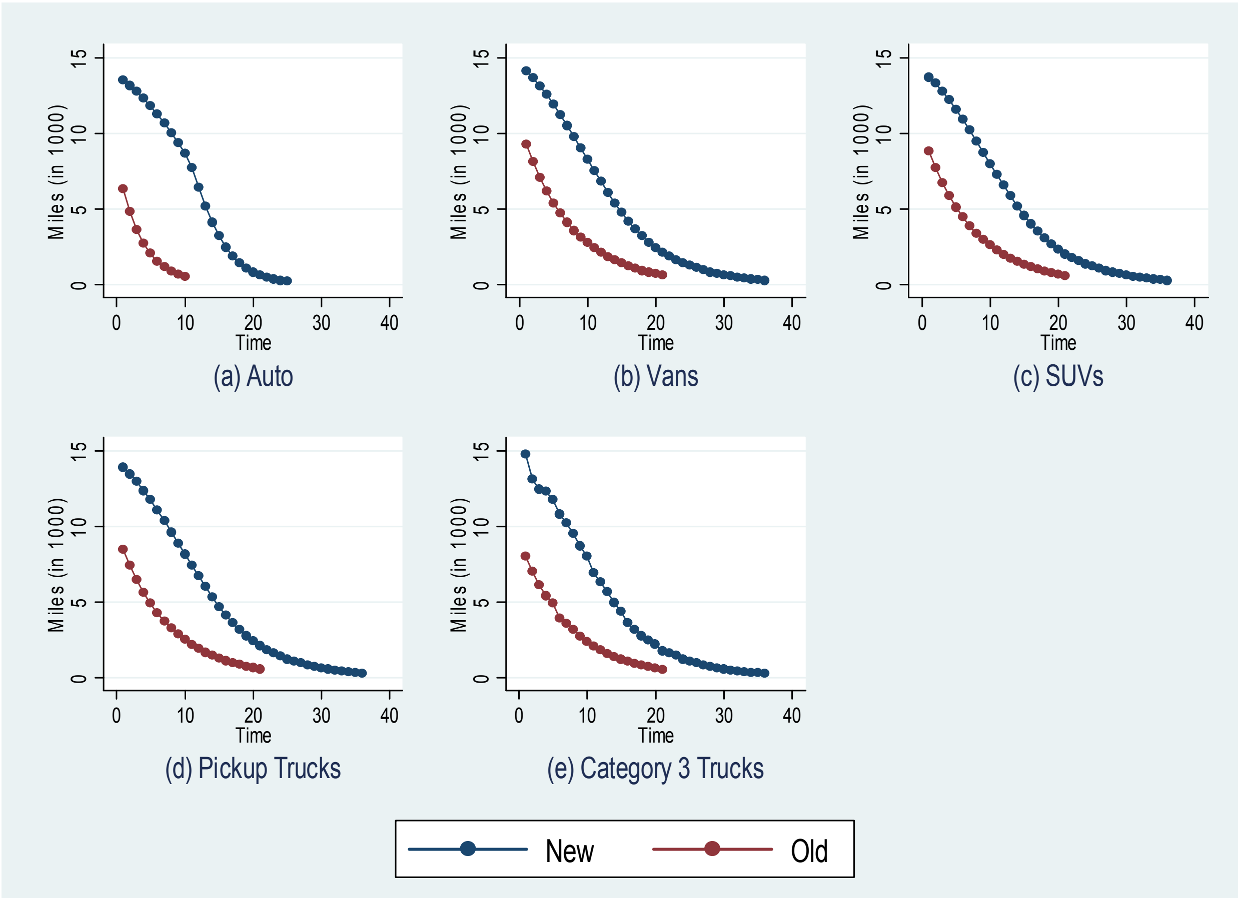
2.6.2 The emissions for the trade-in and replacement vehicles

The pollutants modeled by the EMFAC2011 include reactive organic gases (ROGs, which are in the same class as the EPA's volatile organic compounds (VOCs)), carbon monoxide (CO), nitrogen oxides (NOx), carbon dioxide (CO2), particular matter (PM) including PM10 and

[21] These two cohorts are chosen based on the average ages for the retired and replacement vehicles and the mean residual lifetime D^j of the retired vehicles. Hereafter, these two cohorts are called "representative" cohort. As mentioned earlier, there are 109 and 498 cohorts for the retired and replacement vehicles, respectively. Due to the space limit, only the two representative cohorts are addressed.

[22] Table A2.1 in Appendix shows the numeric VMT values for the trade-in and replacement vehicles of the two representative cohorts.

Figure 2.1: Expected annual VMT schedules by vehicle type (base year 2010)



PM2.5, and oxides of sulfur (SOx). The pollution-reduction effects on all these pollutants are addressed in the current study.

According to the *EMFAC2011-LDV User's Guide (2011)*, the emissions emanating from a vehicle can be distinguished according to the types of emission processes and include running exhaust, idle exhaust, starting exhaust, diurnal emissions, hot soak, running loss, and resting loss (see the definitions in Glossary of Terms). Among these different emissions types, running exhaust and running loss can be regarded as "direct" emissions from a vehicle's movement, while the other types of emissions are regarded as "indirect" emissions because they are not directly associated with a vehicle's driving. In this paper, both "direct" and "indirect" vehicle pollution are estimated for the CARS vehicles. The emissions for each pollutant mentioned above are calculated as follows according to their emission process:

$$ROG\ (TOG) = s \cdot VMT \cdot (RUNEX + RUNLS) + 365 \cdot s \cdot (IDLEX + STREX + DIURN + HTSK + RESTL)$$

$$CO\ (NO_x,\ CO2,\ or\ SOx) = s \cdot VMT \times (RUNEX) + 365 \cdot s \cdot (IDLEX + STREX)$$

$$PM10\ (PM25) = s \cdot VMT \cdot (RUNEX + PMTW + PMBW) + 365 \cdot s \cdot (IDLEX + STREX),$$

where $RUNEX$ and $RUNLS$ (both in grams per mile) refer to the emission factors for running exhaust and running losses, respectively; $IDLEX$, $STREX$, $DIURN$, $HTSK$, and $RESTL$ (all in grams per vehicle per day) refer to the emission factors for idle exhaust, starting exhaust, diurnal, hot soak, and resting losses, respectively; $PMTW$ and $PMBW$ are the factors for PM emissions resulting mainly from tire wear and brake use, respectively; and s is vehicle survival rate. Idle exhaust applies only to heavy-duty vehicles (corresponding to Category 3 Trucks in the study), but not to passenger cars and light-duty vehicles because this variable refers to the emissions created while loading or unloading goods.

From the equations (2) and (3), the emission schedules of different pollutants can be derived for both the retired and replacement vehicles according to the previously defined vehicle cohorts. Figure 2 below demonstrates how the ROG and CO2 emissions evolve as a vehicle ages for the two "representative" cohorts.[23] For the retired vehicles of 16 years old, the decreasing VMTs and survival rates outweigh the increasing ROG emission rates as time passes. As a result, the future ROG emissions for these vehicles exhibit a decreasing trend regardless of its vehicle type as seen in Figure 2. In addition, the magnitude of ROG emission rates determines that Category 3 Trucks produce the most emissions at any given

[23] See footnote 16.

time, while passenger cars produce the least, regardless of pollutant type. Moreover, the pollution patterns for Vans, SUVs, and Pickup Trucks are similar because a same set of survival rates and emissions rates are applies to these types of vehicles and these vehicles on average have close travel demand predicted by the empirical results.

Regardless of vehicle type, Figure 2 also shows that for the vehicles of age 1 the ROG emissions first increase with time, reach to the maximum level at an age between 10 to 12, and decrease again. This observation can be explained by the information contained in Table 8. For a passenger car of model year 2009 (or of age 1), its VMTs and survival rate would decrease a lot when the vehicle was age of 10, but the decrease is completely offset by the increase in their emission rates, see column (5) in Table 8. Hence, the first phase of increasing in ROG emissions is observed. Given the same car, the ROG emissions emitted at its age of 20 would be less than those at its age of 10 because survival rate is the dominant factor to determine the ROG level, see column (6) in Table 8.

In contrast, an increasing phase can not be found with respect to CO2. Table 8 also shows that given a passenger car the emission rates of CO2 tend to be stable overtime, see column (5) and (6). Thus, VMTs and survival rates play a dominant role in determining a car's CO2 emissions levels and the levels tend to be decreasing overtime. More importantly, Figure 2 illustrates that ROG emissions from a car of newer vintage in the near future (say five years) are less than those from a car of older vintage, while CO2 emissions from the former are more than those from the latter. This finding results from the observation that the ROG emission rates of old vintage vehicles dramatically rise, but the CO2 emission rates are relatively stable across different vehicle vintages, see column (7) in Table 8.

ROGs are either emitted from a vehicle's tailpipe or evaporate from a vehicle's fuel system. The vehicles of old vintage are generally equipped with outdated emission control system, as a result, the ROG emissions from one mile's driving by such a vehicle can be much higher than those by a vehicle of new vintage. Although a vehicle, including its emission control system, generally performs worse as the vehicle ages, and fuel is more likely to escape from an older vehicle than a newer one, the magnitude of the ROG emission rate does not dramatically increase over time given the vehicle vintage unchanged. All these facts essentially determine the ROG emission patterns. Furthermore, the emission schedules for both CO and NOx exhibit a similar pattern for ROG because the emissions rates for these two pollutants are also highly inversely related to vehicle vintage.

CO2 emissions in contrast are determined by fuel property and fuel consumption, but are not directly constrained by the vehicle emission control system. The amounts of CO2 from burning a gallon of fuel are dependent on the fuel's carbon contents. Similarly, SO2 emissions are majorly determined by fuel's sulfur contents. Therefore, vehicle age and vintage less directly affect the emission rates of CO2 and SOx than on the rates of the other pollutants mentioned earlier, but they do affect the emissions levels of these two pollutant through their impacts on VMTs. Specifically, a vehicle tends to be driven less and consumes less fuel with aging and is likely to emit less CO2 and SO2 into the air. Lastly, PM10 and PM2.5 are generated mainly as a result of brake use and tire wear. Presumably, the emissions of these two pollutants like CO2, SOx tend to be determined by VMTs are inversely related with vehicle age.

2.6.3 The net pollution effects of the CARS program

The pollution schedules for any cohort of trade-in and replacement vehicles in the CARS program have been derived, and we can obtain the cohort emissions by multiplying the emissions of each cohort by the corresponding cohort counts. Next, the cohort emissions can be aggregated for the replacement vehicles according to their type and age.[24] The emissions of one pollutant for a given vehicle type and age between retired and replacement vehicles, however, are still not comparable because of the difference in vehicle counts. Then, the per-vehicle emissions produced by the retired and replacement vehicles during the residual

[24] Recall that residual lifetime is an additional dimension to define the replacement cohorts.

lifetime of the retired vehicles can be obtained according to vehicle type and age. If these emissions are called "residual" emissions per vehicle thereafter, then Figure 3 and 4 below presents these residuals to us. Again, only ROG and CO2 are chosen as representative pollutants to perform analysis.

Not surprisingly, Figure 3 shows that the "residual" ROG levels per trade-in vehicle first increase with vehicle age, reach maximum levels around vehicle age 20, and decrease at the end of a vehicle's end of life, regardless of the vehicle type. This findings means that a car of age 25 could emit more the "residual" emissions than a car of age 5, with 2010 as base year. As argued earlier, vehicle vintage plays a more important role in determining the magnitudes of ROG emission rates, and thus emission levels.[25] Thus, the "residual" ROG emissions from the vehicles of older vintage could be larger than those from the vehicles of newer vintage. Moreover, the figure also shows that the replacement vehicles generate relatively lower "residual" ROG emissions because the replacements have the latest model years and are equipped with more advanced emission control systems and the function of such systems does not deteriorate dramatically overtime.[26]

In contrast, Figure 4 suggests that the "residual" CO2 emissions decrease with vehicle's aging for both the retired and replacement vehicles. Moreover, new CARS vehicles (except Category 3 Trucks) produce less the "residual" CO2 emissions than the younger retired vehicles but more emissions than the older retired ones.[27] The negative difference arises from the fact that the residual intervals during which the retired and replacement vehicles produce emissions are calculated differently.[28] The positive difference results from the finding that the older retired vehicles are driven less and the CO2 emission rates do not vary significantly

[25]For example, the emission rate of ROG running exhaust is 0.3687 gram per mile for an automobile of model year 1985 (or of age 25). This amount is 34.14 times the rate for an automobile of model year 2005 (or of age 5), which equals 0.0108 gram per mile.

[26]For example, the ROG emission rate for an automobile of model year 2005 would be 0.0223 gram per mile when the vehicle reached age of 25, a decent increase compared to the current emission rate.

[27]Have the CARS program had Category 3 Trucks of age 4 or 5, the CO2 emissions from these vehicles would be greater than those from the replacement vehicles.

[28]Recall, the intervals are $\left(T^i - t^i\right)$ and D^j for the retired and replacement vehicles, respectively, and the former on average is longer than the later.

across vehicle age and vintage.[29]

Now, the emission levels of each pollutant can be aggregated at an upper lever according only to vehicle type. In order to make a comparison, per vehicle pollution levels are calculated, and then the difference in the mean pollution levels between the retired and replacement vehicles can be obtained as shown in Figure 5. The figure demonstrates that the CARS program achieves per vehicle pollution reductions in ROG, TOG, CO, and NOx compared to the retired vehicles across the five vehicle types. This finding is not surprising because replacement vehicles are estimated to produce less per vehicle emissions of these four pollutants regardless of its type and vintage as shown in Figure 3. Moreover, per Passenger Car has the lowest pollution gains relative to other vehicle types because the retired vehicles have shorter residual lifetime. Per Category 3 Truck has the highest gains because the magnitudes of the emission rates for the pollutants of interest are higher for the retired vehicles of this category relative to those of the other vehicle types. Per vehicle emission gains from Van, SUV, and Pickup Truck are approximately equal and lie between the lowest and the highest.

In contrast, Figure 5 shows that replacement vehicles produce more per vehicle emissions than retired vehicles with respect to the pollutants CO2, SOx, and PM10. Again, VMTs compared to other factors have more influence to determine the emissions of these pollutants and replacement vehicles tend to have higher travel volume relative to their retired ones, and thus the rise in per vehicle pollution is predicted. Passenger Car and Category 3 Truck are likely to produce higher per vehicle losses in terms of CO2, SOx, and PM10, which is explained by the shorter residual lifetime of the retired car and bigger magnitudes of the emission rates for the truck, respectively. Although the emissions of PM2.5 are positively related to VMTs, the tiny magnitudes of PM2.5 emission rates cause the residual lifetime of the retired vehicles to be a dominant factor to determine its pollution levels. On average, the CARS Passenger Cars have much shorter residual time compared to other types of vehicles.

[29]For example, the emission rate of CO2 running exhaust is 384.7986 grams per mile for an automobile of model year 1985, and is only 1.10 times the rate for an automobile of model year 2005, which equals 349.8002 grams per mile.

Thus, only PM2.5 losses per Passenger Car are observed.

Lastly, the predicted emissions can be aggregated at an topmost level and compared according to retired and replacement vehicles. Figure 6 shows that the net pollution gains induced by the CARS program occur for ROG, TOG, CO, NOx, and PM2.5 while the losses occur for CO2, SOx, and PM10.

2.6.4 The effects under alternative assumptions for VMTs of replacement vehicles

Based on the structural model of equations (1) and (2), the VMT schedules for the CARS vehicles and associated pollution have been estimated. For ease, the VMTs and relevant pollution are called "model-predicted" VMTs and pollution. The current study assumes that vehicle travel demands are affected only by household and vehicle characteristics. Once one or more of these characteristics, say vehicle age and fuel economy, have changed, the travel demands change accordingly. Some scrappage studies, however, argue that a driver might not change his travel behavior even after replacing his old vehicle with a new vehicle; and thus, these studies assume that a replacement vehicle will be driven for the same number of miles as its paired old vehicle was being driven before it was traded in; for example, see Antweiler and Gulati (2011) and Sandler (2012).

However, the first alternative assumption is questionable because significant changes in vehicle attributes such as vehicle vintage, fuel efficiency, and even vehicle type, have occurred as a result of the CARS program's requirements, and all these changes take effects on VMTs. Therefore, using the VMTs of old vehicles as those of the new vehicles could result in underestimating the pollution produced by the new vehicles. Nevertheless, the pollution under the first alternative assumption is estimated because the results can be used as the lower boundary of the pollution produced by the replacement vehicles.

Second, replacement vehicles are often assumed to be driven at the fleet average VMTs; for example, see Li et al. (2013). This assumption is more likely to be verified than the first one in terms of evaluating the CARS program. If a driver did drive a replacement vehicle at the fleet average, the “model-predicted” pollution of the replacement vehicle could be regarded as the upper boundary of the estimation because the participating new vehicles have higher fuel economy and “model-predicted” VMTs than the fleet average.

Table 9 presents the environmental effects of the CARS program under three different assumptions. Unsurprisingly, the pollution levels of the new vehicles calculated under Assumption 3 (fleet average VMTs) are constrained by the upper limit under Assumption 1 (“model-predicted” VMTs) and the lower limit under Assumption 2 (retired vehicle VMTs). In other words, the pollution reductions induced by the CARS program are the greatest under Assumption 2 (or the induced pollution increases are the smallest), while the reductions are the smallest under Assumption 1 (or the increases are the greatest).

More specifically, the emissions of ROG, TOG, CO, NOx, and PM2.5 drop due to the implementation of the CARS program, while the emissions of CO2, SOx, and PM10 increase under Assumption 1 and 3. However, the emissions of all pollutants are predicted to decrease under Assumption 2. The smallest travel demands are assumed under Assumption 2 and applied to the replacement vehicles, which can explain the difference in terms of pollution changes. Moreover, Table 9 also shows that VMTs have more influential impacts on the CO2 pollution of the replacement vehicles than other types of vehicle pollution. The magnitudes of CO2 pollution vary significantly across different VMTs assumptions.

The monetary values of the corresponding pollution gains and losses are calculated by assuming that the average costs per ton of ROG, CO, NOx, CO2, SOx, PM10, and PM2.5 are \$180, \$74.5, \$250, \$177, \$970, \$170, and \$1170, respectively. More specifically, the average costs of ROG, NOx, SOx, PM10, and PM2.5 are taken from the median marginal damage in Muller and Mendelsohn (2009); the costs of CO are the midpoint of the range estimated by McCubbin and Delucchi (1999); and the costs of CO2 are from Beresteanu and Li (2011).

Given the assumption of "model-predicted" VMTs, Table 9 shows that the emission reduction is estimated as 95%, 90%, 94%, and 7% for ROG, CO, NOx, and PM2.5, respectively, while 20%, 16%, and 16% increase in CO2, SOx, and PM10 are predicted, respectively, for the 76,514 Californian vehicles participating in the CARS program. Table 9 also presents that the monetary gains resulting from the reductions of ROG, NOx, CO, and PM2.5 are $1.07 million, $2.99 million, $1.55 million, and $0.01 million, respectively, while the monetary losses from the increases of CO2, SOx, and PM10 are $82.43 million, $0.004 million, and $0.007 million, respectively. Thus, the positive gains are completely offset by the increased CO2 emissions, with a loss of $76.82 million at an aggregate level. When this amount is converted to per vehicle term, an individual CARS transaction is found to lead to a net loss of approximately $1003.9.

For the best scenario, the net gain would be $35 million (or $458 per vehicle). For the middle scenario, the losses would be $60.2 million (or $787.2 per vehicle). Therefore, it is concluded that the pollution reduction effects of the CARS program could be over estimated given that a household would not change its driving demand is assumed. In addition, if the damage from a tonne of CO2 is assumed to be close to $50, the conclusion would not change, see the last column in Table 9. The program is likely to play a negative role in reducing pollution. Li et al. (2013) examine the program effect on employment using the measure of "job-year". To my best knowledge, so far no studies directly address the program effect on employment rate. If the program raised the employment rate through shifting the future vehicle purchases to the current period, it would result in additional monetary gains or less losses.

2.6.5 A discussion on adverse selection

When evaluating an accelerated vehicle retirement program, the issue of adverse selection must be addressed. A vehicle owner knows the quality and performance of his vehicle better than those administering such a program. The owner of a vehicle in poor condition would have soon traded in his vehicle in the absence of such a program. However, this owner could take advantage of his superior knowledge of his vehicle and had an incentive to participate a vehicle retirement program. In the literature, this phenomenon is known as “adverse selection”.

The CARS program had a unique feature that reveals the extent of the adverse selection. Dealers in the CARS program sent new vehicle purchasers the questionnaire for the “Survey of Consumer Response to CARS Initiative”. 143,998 CARS purchasers participated in this voluntary survey. The first question asked if a participant would still have traded in his old vehicle in the absence of this program.

The responses of the survey participants are summarized as follows: 16,801 new vehicle purchasers answered “yes” to this question, while 127,026 answered “no”; thus, about 11.68 percent of 143,827 purchasers who responded to this question admitted that they would have soon traded in their vehicle. Moreover, if this percentage were an accurate estimate of the “adverse selection” and could be applied to California’s program participants, 8,938 out of the total 76,514 transactions would be in question.

Previous studies concerning the issue of adverse selection in a scrappage program argue that the transactions in question tend to negatively affect the cost-effectiveness of a vehicle retirement program as the vehicles involved in these transactions would have been scrapped soon anyway without being payed any incentive to the owners; for example, see Sandler (2012).

However, the CARS program had strict fuel-efficiency improvement requirements, which might have led the program participants to choose a vehicle with a higher fuel economy than a vehicle that would have been chosen without being offered the $3,500 or $4,500 CARS incentive, a significant trade-in bonus.

Of course, the binding requirements for improvements in fuel efficiency also applied to the vehicle owners in the case of adverse selection and could have changed their decisions about vehicle type and/or fuel economy. Choosing a vehicle with higher fuel efficiency generally results in a pollution reduction, even under the existence of adverse selection. This survey provides information that allows the real decisions about vehicle type to be compared with the counterfactual decisions in the absence of the CARS program.

The second survey question asked what type of a new or used vehicle a participant would have purchased when disposing of his vehicle if he had not planned to purchase another vehicle at that time. Again, Table 9 summarizes the answers from all the survey respondents, showing that the counterfactual decisions about vehicle type are similar no matter whether a participant planned to purchase a used or a new vehicle.

However, when these decisions are compared to the real ones made under the CARS program, more passenger cars are found to be chosen by participants in reality, around 24.3 percent more than in the counterfactual situation. Moreover, the increased proportion is achieved by transferring the sales of the larger vehicles including Vans, SUVs, and Pickup Trucks into the sales of passenger cars under the CARS program.

More interestingly, if the CARS program had not existed, some customers would not have purchased any vehicle when disposing of their old vehicles. However, the significant amount of trade-in bonus might have triggered some new vehicle purchases that would not have occurred otherwise, and that also increased future pollution. This phenomenon is called policy “overshooting” by the current study. The issues of adverse selection and potential changes in vehicle purchasing decisions could be studied in future research.

2.7 Conclusion

The CARS participants replaced their old gas guzzlers with the vehicles of newer vintages, higher fuel efficiency, and even different vehicle types. Therefore, it might not be appropriate to assume that the program participants would not change their driving behavior or just drive at the fleet average miles after purchasing the new vehicles. However, these two assumptions are commonly adopted by the scrappage literature when evaluating an Accelerated Vehicle Retirement program.

This paper followed the traditional framework from the urban economics literature to examine vehicle travel behavior; in addition, valid instruments were used to control for the potential endogeneity problem of fuel efficiency. A big fuel gap between the retired and replacement vehicles were created by the CARS program and fuel efficiency was found to have much smaller impacts on VMTs under IV estimation method compared to OLS method. Thus, accounting for the endogeneity could help provide a more accurate estimation of VMTs, and thus the associated vehicle pollution.

Using the 2009 NHTS as a primary dataset, the current study predicted the travel demand for the NHTS vehicles based on the surveyed household and vehicle characteristics. Next, the VMTs of the CARS vehicles were derived by matching them with the NHTS vehicles according to their vehicle attributes. Thus, the empirical analysis performed by the current study relied on the attributes of the vehicles actually scrapped by the CARS program but not heavily on the traditional assumptions adopted by the scrappage literature.

Combining the "model-predicted" VMTs of the Californian CARS vehicles with the EMFAC2011 emission factors, the current study predicted a reduction of emissions of ROG, CO, NOx, and PM2.5 by 95%, 90%, 94%, and 7%, respectively, while the program resulted in an increase of emissions of CO2, SOx, and PM10 by 20%, 16%, and 16%, respectively. The CARS program led to a loss of $76.8 million at an aggregate level (or $1003.9 per vehicle) with the gains from the reduced emissions of the relevant pollutants completely offset by the increase of the global pollutant CO2.

In order to determine if the results of previous studies could be used as references in this current study, the environmental effects of the CARS program were also examined under the other two scenarios assumed in the scrappage literature. If the fleet average VMTs were assumed, the program was found to have led to the losses of \$60.2 million (or \$787.2 per vehicle). However, net environmental gains were obtained if the replacement vehicles were assumed to have same VMTs as its paired retired vehicle at the trade-in year. The gains under the best scenario were calculated as \$35 million (or \$458 per vehicle). Therefore, it concluded that different assumptions on travel demand could significantly affect the environmental evaluation of the CARS program.

The current study also demonstrated that the emission rates played a more dominant role in determining the emissions of ROG, TOG, CO, and NOx because the emissions of these four vehicle pollutants produced by one mile's driving were strongly positively correlated with vehicle vintage, i.e., inversely correlated with the performance of a vehicles' pollution control system. The replacement vehicles equipped with more advanced pollution control system were much cleaner, so they were likely to produce much less emissions of the relevant pollutants than the trade-in vehicles even though they had higher VMT volumes.

In contrast, the emissions of CO2, SOx, PM10, and PM2.5 were affected by VMTs because fuel consumption together with a fuel's carbon and sulfur contents can determine the emission levels of CO2 and SOx, and VMTs and fuel consumption were closely related. Similarly, VMTs took a significant effect on the emissions of PM10 and PM2.5, as these two pollutants were produced mainly as a result of tire wear and brake use. Due to the higher VMT volume, the new CARS vehicles were more likely than the old vehicles to emit more CO2, SOx, PM10, and PM2.5. Therefore, it was more possible to observe that the CARS program would lead to an increase in the emissions of these four pollutants but a reduction of ROG, TOG, CO, and NOx emissions, as illustrated in the current study.

Knittel (2009) also examined the CARS program and predicted a reduction in CO2 emissions, which was opposite to the conclusion obtained by the current study. The contradiction mainly resulted from the different assumptions on the driving volume of the retired vehicles. Knittel (2009) assumed that all retired vehicles were driven constantly at 12,000 miles, annually, until they were scrapped. However, the current study found that the retired vehicles initially were driven at 9,722 miles (based on "model-predicted" VMTs) and were driven less and less as they were getting old. Therefore, Knittel (2009) presented higher estimated pollution levels from the retired vehicles and concluded an environmental gain induced by the CARS program.

Li et al. (2013) also concluded that the CARS program achieved a positive environmental gain by using the fleet average VMTs from Lu (2006) as VMT schedules for both the retired and replacement vehicles. However, the fleet average tends to overstate the travel demand for the retired vehicles; and on the other side, the fleet average is likely to underestimate the demand for the replacements vehicles. Use of the fleet average, however, can not explain why their empirical results were different from ours because assuming the average or "model-predicted" VMTs only slightly changed the empirical results obtained by the current study, see Table 9. Essentially, the difference in conclusion can be interpreted by the observation that Li et al. (2013) took into account the program's effects on new vehicle sales. They argued that the program affected the new vehicle sales by shifting the future purchasing demands into the program effective period. After removing the pollution produced by the replacement vehicles belonging to the shifted sales, they found that the program was still costly to achieve a positive pollution reduction.

The current study found that the CARS program potentially did not result in the CO2 emissions and an environmental gain even with taking into account its effects on the pollution of criteria pollutants. However, this study did not account for the shifting vehicle demands, i.e., counterfactual vehicle sales in the absence of the CARS program. Had the pollution from the counterfactual been removed, the program's environmental benefit would be larger than that obtained by the current study. The merits of the program in terms of economic stimulus were left for the future research. Lastly, this paper identified the existence of adverse selection by using the unique feature of the CARS survey. Unlike other scrappage literature, this study found that the vehicle transactions in the case of adverse selection still had some potential effects on pollution reduction because the purchasing decisions about new vehicles and fuel economy of the participating vehicles were also affected positively by the CARS program's requirements.

Table 2.6: Variable summary statistics (N=277,195)

	mean	s.d.	min	max
Annual vehicle miles traveled (units of 1000)	11.35	9.10	0.7	165
Vehicle fuel efficiency (mpg)	20.26	5.37	5.9	50
Fuel cost (dollars per gallon)	3.07	0.14	1.2	4
Exogenous household characteristics				
HH income (units of 10,000 dollars)[1]	7.75	5.55	0.3	17
HH size	2.63	1.27	1	14
Count of vehicle's primary drivers	1.54	0.71	1	14
Count of HH workers	1.16	0.95	0	6
Adults with children	0.33	0.47	0	1
Adults with no children	0.31	0.46	0	1
Race of HH respondent is White	0.88	0.33	0	1
Race of HH respondent is African American or Black	0.05	0.22	0	1
Race of HH respondent is Asian only	0.02	0.14	0	1
Race of HH respondent is American Indian or Alaskan Native	0.01	0.08	0	1
Race of HH respondent is Native Hawaiian or other Pacific	0.00	0.05	0	1
Race of HH respondent is Hispanic	0.02	0.15	0	1
Race of HH respondent is Multiracial	0.01	0.08	0	1
Number of housing units per square mile (units of 1000)	1.28	2.23	0.1	30
Home is owned	0.92	0.27	0	1
Home locates in a MSA with rail	0.16	0.37	0	1
Home locates in an urbanized area	0.67	0.47	0	1
Vehicle attributes				
Vehicle age	8.11	5.24	1	24
Automobiles	0.52	0.50	0	1
Vans	0.08	0.28	0	1
SUVs	0.19	0.39	0	1
Pickup Trucks	0.21	0.40	0	1

Note: 1. HH income is calculated as the midpoints of the 18 income categories in the NHTS with $170,000 and $35,000 assigned for the top category and missing incomes, respectively (these two numbers were adopted by Brownstone and Golob (2009)). 2. Following Greene et al. (1999), the vehicles with annual fuel consumption either less than 25 gallons or greater than 6000 gallons are eliminated. This process is applied to remove the vehicles not in use or with too much use.

Table 2.7: Structural regression results

	(1) IV estimate	(2) s.e.	(3) OLS estimate	(4) s.e.
Dependent variable	Annual vehicle miles traveled (units of 1,000)			
Vehicle fuel efficiency (mpg)	0.0337***	(0.0101)	0.632***	(0.00398)
Fuel cost (dollars per gallon)	-0.506***	(0.136)	-0.730***	(0.129)
HH income (units of 10,000 dollars)	0.0536***	(0.00361)	0.0692***	(0.00343)
HH size	0.351***	(0.0240)	0.397***	(0.0229)
Count of vehicle's primary drivers	-0.193***	(0.0277)	-0.285***	(0.0262)
Count of HH workers	0.652***	(0.0260)	0.398***	(0.0245)
Adults with children	2.058***	(0.0657)	1.466***	(0.0621)
Adults with no children	1.666***	(0.0519)	1.234***	(0.0492)
Race is White	-0.0254	(0.142)	0.164	(0.135)
Race is African American or Black	0.363*	(0.162)	0.795***	(0.154)
Race is Asian only	-0.696***	(0.189)	-0.914***	(0.180)
Race is American Indian or Alaskan Native	0.572*	(0.256)	0.628**	(0.243)
Race is Native Hawaiian or other Pacific	0.0987	(0.378)	0.0370	(0.361)
Race is Hispanic	0.220	(0.188)	0.289	(0.177)
Race is Multiracial	0.955***	(0.274)	0.853**	(0.261)
Residential density	-0.101***	(0.00901)	-0.107***	(0.00850)
Home is owned	-0.801***	(0.0702)	-0.542***	(0.0667)
Home locates in a MSA with rail	-0.241***	(0.0539)	-0.309***	(0.0514)
Home locates in an urbanized area	-0.982***	(0.0407)	-0.889***	(0.0389)
Vehicle age	-0.227***	(0.0289)	0.154***	(0.0271)
Vehicle age square	-0.00885**	(0.00300)	-0.0300***	(0.00284)
Vehicle age cubic	0.000376***	(0.0000886)	0.000820***	(0.0000842)
Auto	-0.563***	(0.0813)	-4.456***	(0.0525)
Vans	0.344***	(0.0789)	-1.231***	(0.0718)
SUVs	0.191**	(0.0584)	-0.320***	(0.0552)
Constant	13.34***	(0.489)	2.423***	(0.440)
N	236,933		244,084	
R2	0.083		0.158	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.2: ROG and CO2 emission schedules by vehicle type

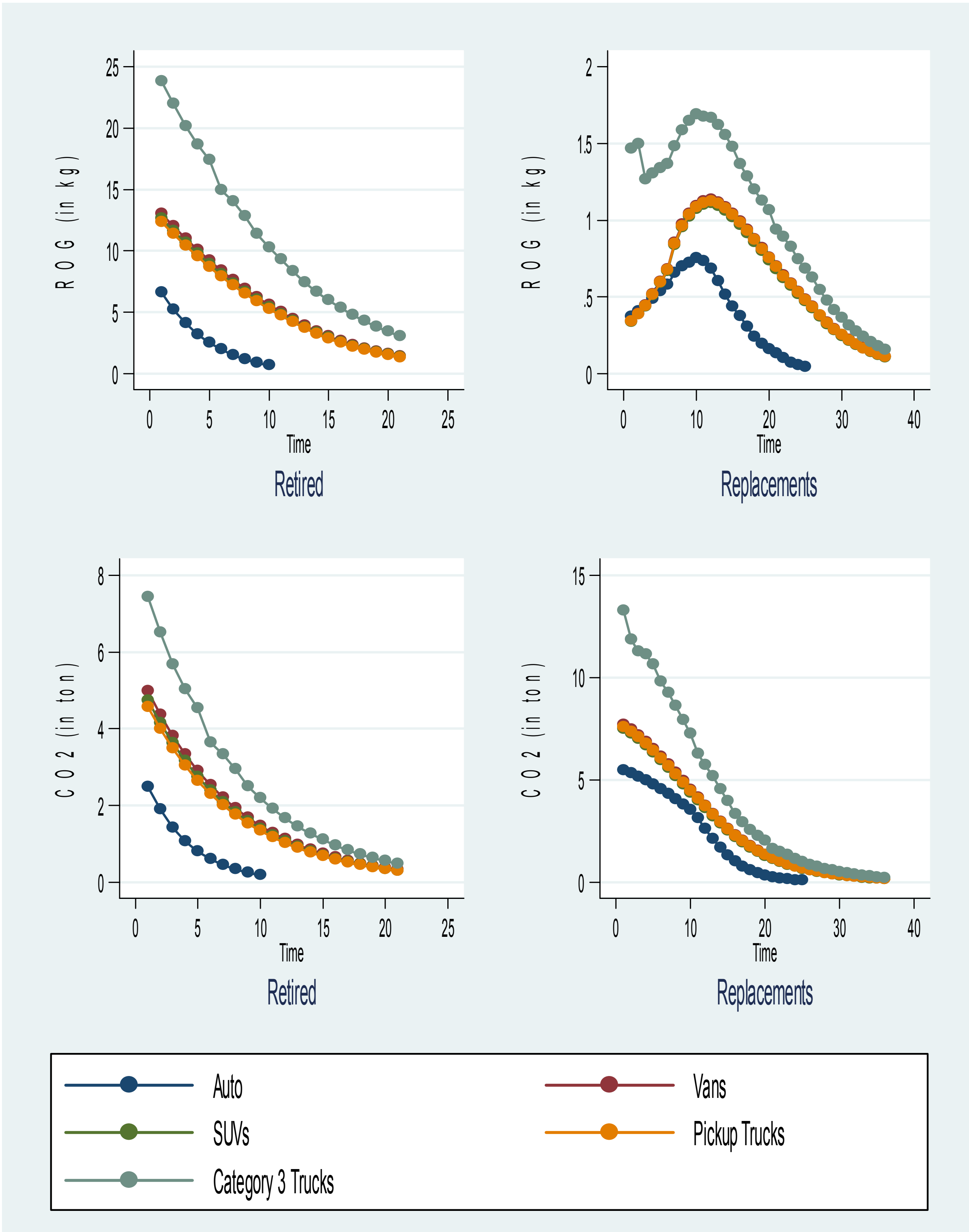
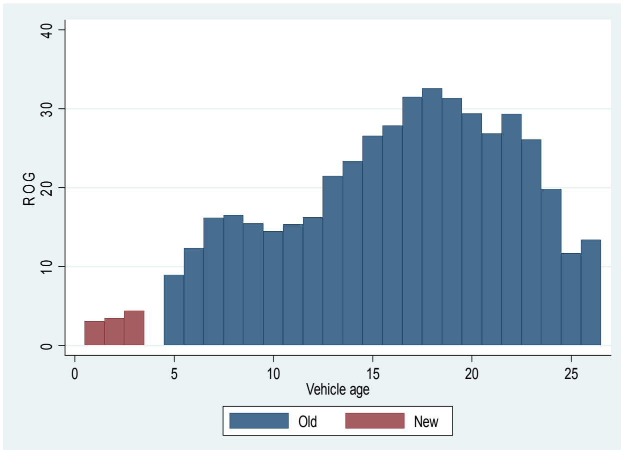


Table 2.8: ROG emission rates schedule (passenger cars, calendar year 2010)

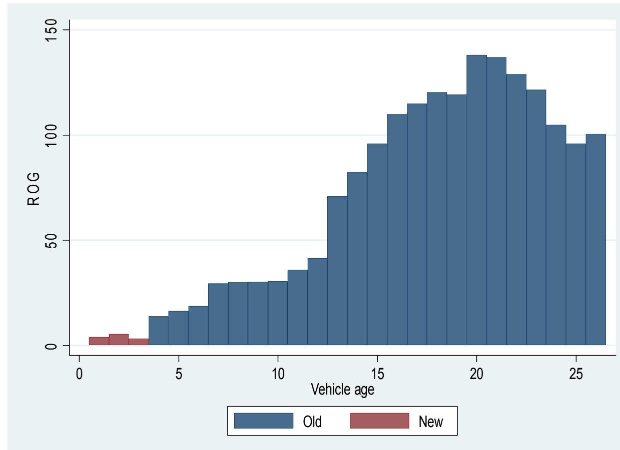
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model year		2009		1994		Ratio	
Vehicle age	1	10	20	16	(2)/(1)	(3)/(2)	(4)/(1)
VMT	13662.91	11016.68	8672	8015.74	0.81	0.79	0.59
Survival rate	0.990	0.787	0.092	0.787	0.79	0.12	0.80
ROG							
Running exhaust	0.007	0.012	0.026	0.142	1.76	2.15	20.89
Starting exhaust	0.239	0.374	0.604	7.863	1.56	1.62	32.86
Diurnal	0.029	0.112	0.272	2.276	3.89	2.41	78.78
Hot soak	0.040	0.411	0.982	3.098	10.21	2.39	77.02
Running loss	0.012	0.041	0.083	0.250	3.44	2.04	21.00
Resting loss	0.020	0.123	0.308	1.096	6.27	2.50	55.65
CO2							
Running exhaust	353.21	352.55	354.00	338.26	1.00	1.00	0.96
Starting exhaust	485.91	468.78	435.53	418.94	0.96	0.93	0.86

Note: For the definition of different emission types, see Appendix. Idle exhaust is not applicable to passenger cars and not included in the table.

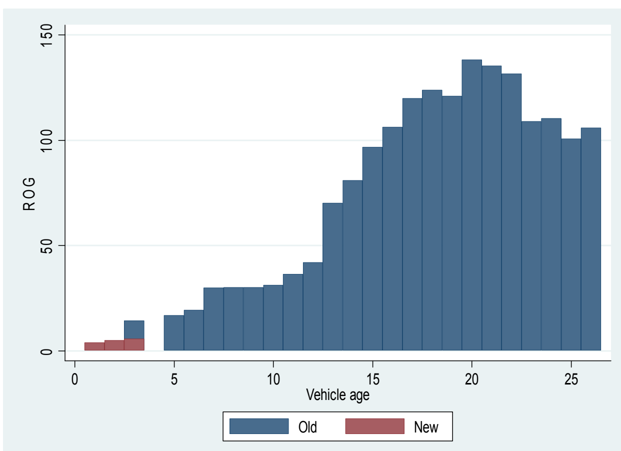
Figure 2.3: Per-vehicle ROG emissions during the residual lifetime of the trade-in vehicles by vehicle type and age (kg, calendar year 2010)



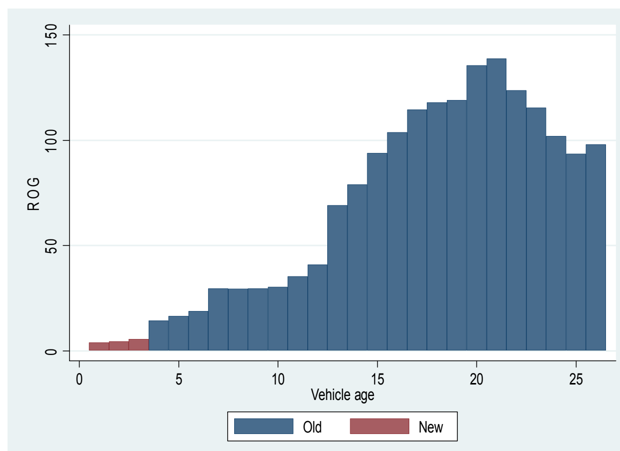
(a) Automobiles



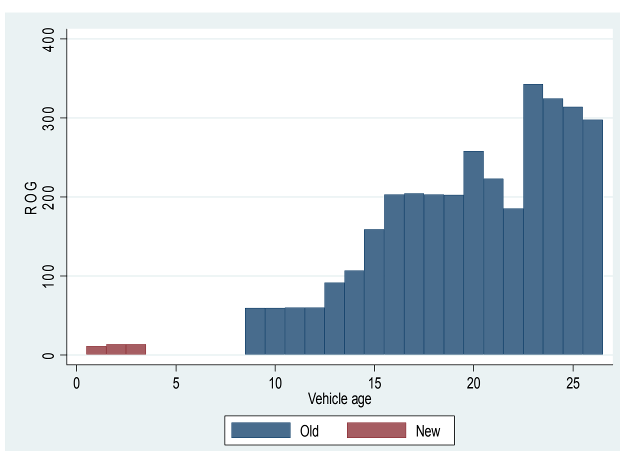
(b) Vans



(c) SUVs

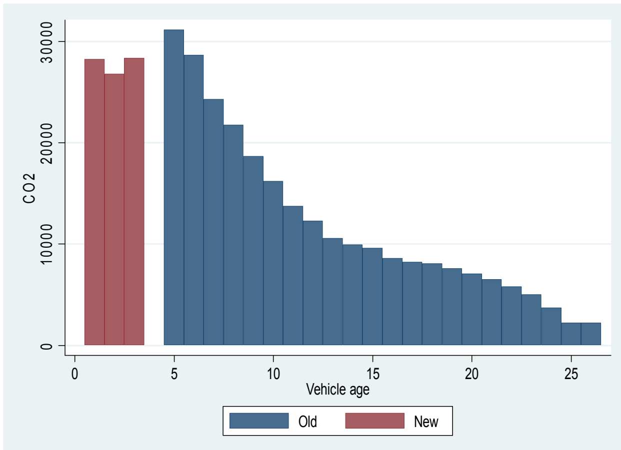


(d) Pickup Trucks

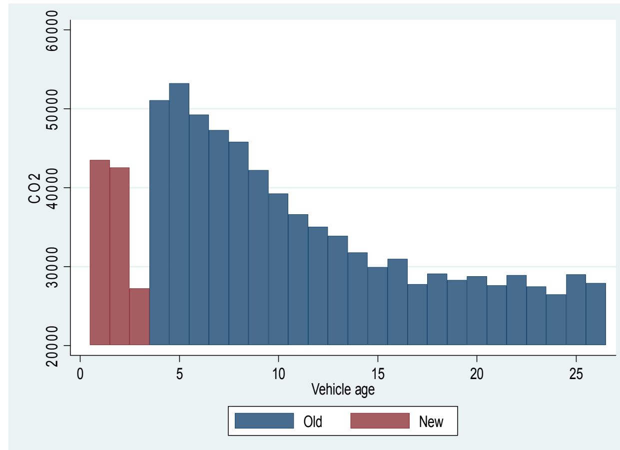


(e) Category 3 Trucks

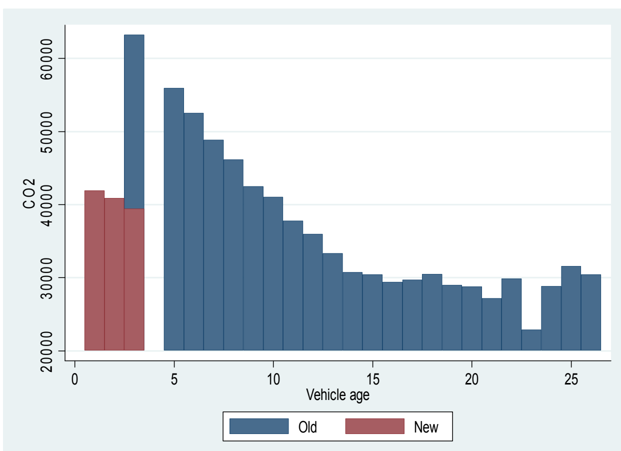
Figure 2.4: Per-vehicle CO2 emissions during the residual lifetime of the trade-in vehicles by vehicle type and age (kg, calendar year 2010)



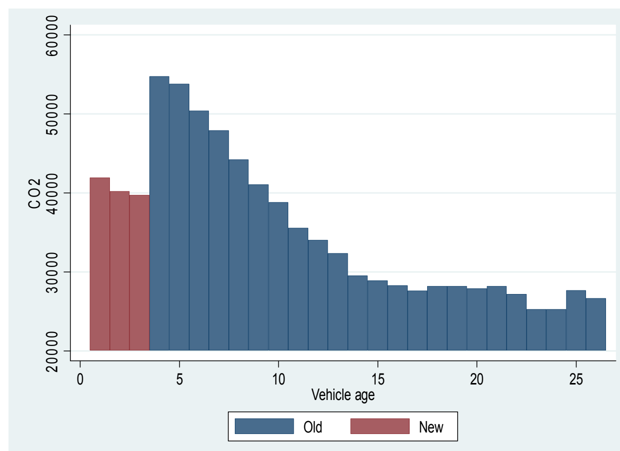
(a) Automobiles



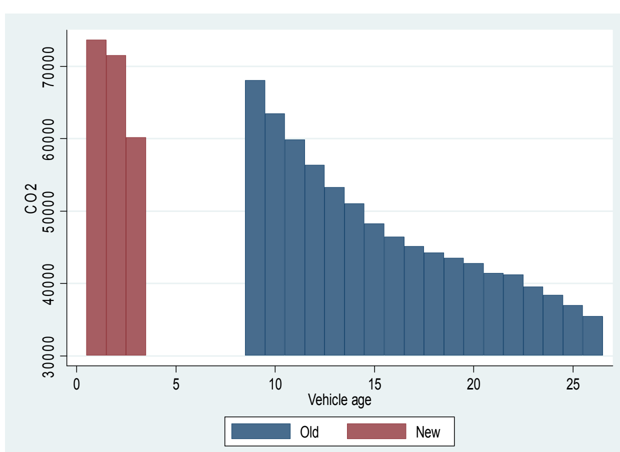
(b) Vans



(c) SUVs

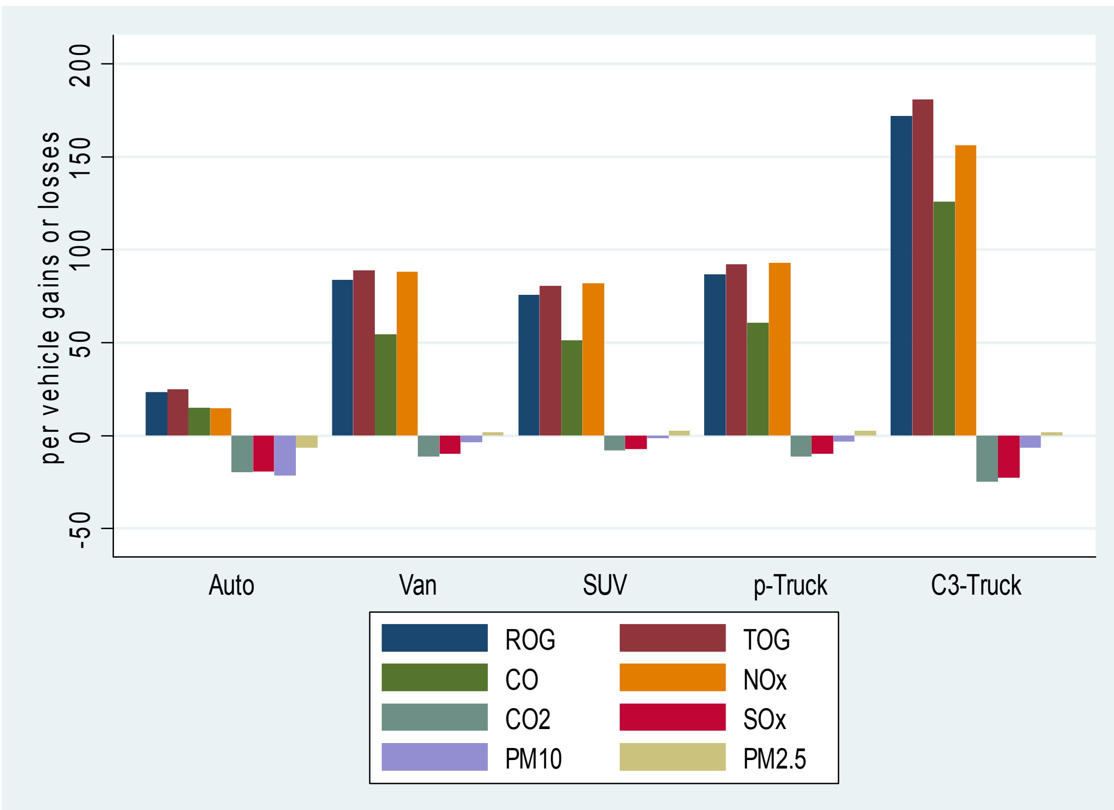


(d) Pickup Trucks



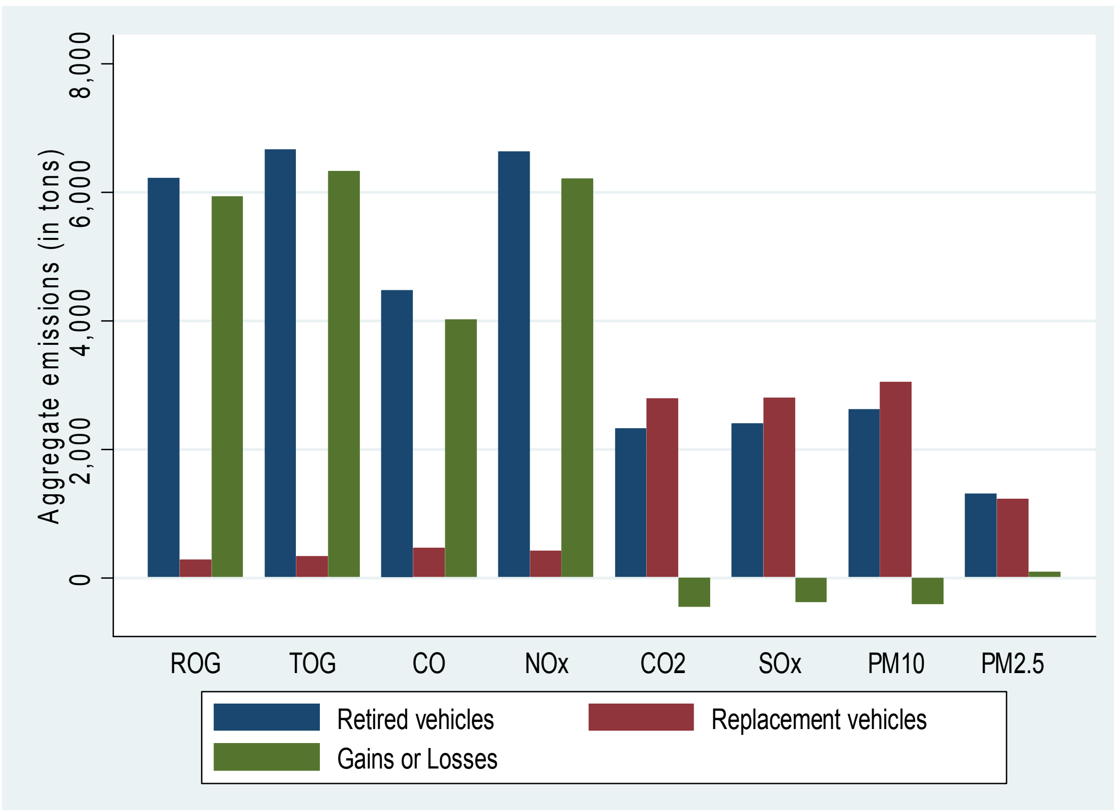
(e) Category 3 Trucks

Figure 2.5: per vehicle pollution gains (or losses) by vehicle types and pollutants (kg)



Note: The magnitudes of CO, CO2, SOx, PM10, PM2.5 are scaled down by 10, down by 1,000, up by 100, up by 10, and up by 10, respectively.

Figure 2.6: Aggregated emissions effects of the CARS program (tons)



Note: The magnitudes of CO, CO2, SOx, PM10, PM2.5 are scaled down by 10, down by 1,000, up by 100, up by 10, and up by 10, respectively.

Table 2.9: Environmental effects of the CARS program under different scenarios (tons)

Pollutant	ROG	CO	NOx	CO2	SOx	PM10	PM2.5
Old vehicle	6217.1	44764.9	6637.7	2329867.0	24.0	262.1	131.1
Assumption 1: "model-predicted" VMTs							
New vehicle	283.9	4610.0	424.4	2795560.0	28.0	304.3	122.1
	-95%	-90%	-94%	20%	16%	16%	-7%
Assumption 2: retired vehicle VMTs							
New vehicle	247.7	3808.0	343.5	2164392.0	21.7	233.3	93.7
	-96%	-91%	-95%	-7%	-10%	-11%	-29%
Assumption 3: fleet average VMTs							
New vehicle	276.8	4473.9	410.8	2702005.0	27.0	292.3	117.3
	-96%	-90%	-94%	16%	12%	12%	-10%

Pollutant	ROG	CO	NOx	CO2	SOx	PM10	PM2.5	CO2
Cost ($ per ton)	180	74.5	250	177	970	170	1170	50
Assumption 1: "model-predicted" VMTs								
Difference (million)	1.07	2.99	1.55	-82.43	-0.004	-0.007	0.01	-23.28
Aggregate (million)	-76.82							-17.67
Per vehicle (dollar)	-1003.94							
Assumption 2: retired vehicle VMTs								
Difference (million)	1.07	3.05	1.57	29.29	0.002	0.005	0.044	0.005
Aggregate (million)	35.04							14.02
Per vehicle (dollar)	457.95							
Assumption 3: fleet average VMTs								
Difference (million)	1.07	3.00	1.56	-65.87	-0.003	-0.005	0.016	-18.61
Aggregate (million)	-60.23							-12.97
Per vehicle (dollar)	-787.21							

Table 2.10: A comparison of counterfactual and real decisions on vehicle type

Type	Counterfactual decision				Real decision	
	used		new		new	
	count	proportion	count	proportion	count	proportion
Auto	23480	0.470	37810	0.468	54575	0.713
Vans	2597	0.052	3972	0.049	1726	0.023
SUVs	13532	0.271	23244	0.288	13658	0.179
Ptrucks	9310	0.186	13959	0.173	6555	0.086
Other	1030	0.021	1812	0.022		
total	49949		80797		76514	

3 The Direct Rebound Effect: Evidence from the 2009 National Household Travel Survey

3.1 Introduction

The US Corporate Average Fuel Economy (CAFE) standards have imposed increasingly stringent requirements on vehicle fuel economy. The average fuel economy of cars and trucks increased by 102.2 and 67.2 percent, respectively, over the period of 1975 to 2012.[1] The improvement of fuel efficiency is motivated by the desire to reduce fuel consumption and vehicle carbon emissions. However, the improved efficiency leads to a reduced per-mile cost of driving, thereby increasing household real income. If travel service is a normal good, additional demand for the service will be produced due to income and substitution effects. The additional travel demand is called the direct rebound or "take back" effect because it may offset the potential fuel saving that otherwise could be obtained.

Moreover, a higher real income level will also encourage more consumption of other products. The energy incurred to produce these extra products is called the indirect rebound effect of fuel efficiency improvement. Producers and consumers respond to a change in the efficiency of

[1] Source: US EPA, Light-duty automotive technology, carbon dioxide emissions, and fuel economy trends: 1975 through 2012. March, 2013.

producing an energy service by adjusting supply and demand in all sectors. The economy-wide responses, measured mainly by the adjustment of energy prices, are defined as the general equilibrium effect.[2] Knowing the magnitude of the rebound effect is critical for determining if a technological innovation will save energy and reduce emissions. In some extreme cases, the energy consumption induced by the additional demand for energy service could completely offset the energy saving resulting from an efficiency improvement, and then the "backfire" phenomenon will occur Sorrell et al. (2009).

Most literature on the rebound effect has examined the direct effect because it is relatively difficult to quantify both the indirect and general equilibrium effects. The related empirical studies can be distinguished by the type of data used. Aggregate studies obtain the rebound effect based on national or state-level data and arrive at relatively consistent results, with about a +0.1 rebound effect for the short run (one year) and +0.2 to +0.3 for the long run Greene et al. (1999). However, most of the earlier aggregate studies did not control for the endogeneity of fuel efficiency when evaluating the rebound effect.

Small and Dender (2007) argue that fuel prices, the regulatory environment, and a household's expected amount of driving can all affect vehicle fuel efficiency. In general, households have their expectation about the vehicle miles traveled (VMTs), and thus a household expecting to drive a long distance regularly may be more likely than other households to choose a vehicle with high fuel efficiency. Therefore, the observed highly positive relationship between fuel efficiency and VMTs may be just an embodiment of the vehicle-selection mechanism. As a result, the interdependence between fuel economy and VMTs should be taken into account in order to provide an unbiased estimate of the rebound effect. Furthermore, whether or not a study controls for the fuel efficiency endogeneity may be one reason why micro-studies based on household-level data present much more diverse estimates of the effect, ranging from 0 to about +0.9. These results mean that a 100 percent improvement of fuel efficiency

[2]For more information on the distinctions between the different types of rebound effects, see Greene et al., 1999.

could produce additional VMTs varying from zero to 90 percent at most.

Moreover, the rebound effect studies can also be distinguished by whether or not they take into account the interactions between multiple household vehicles. To some extent, the different vehicles within a household are substitutes, and an increase in VMTs due to improved fuel efficiency for one household vehicle may reduce the use of the other household vehicle(s). Hence, treating multiple vehicles within a household independently could result in overestimating the direct rebound effect. Greene et al. (1999) state that the share of multiple-vehicle households increased from 22 to 55 percent from 1960 to 1990 and reached 71 percent in 2009.[3] Arising from the increasing number of household vehicles, the overestimation of the rebound effect would exaggerate without controlling for the vehicle substitution effects.

The current study examines the relationship between VMTs and fuel efficiency by adopting the econometric model proposed by Greene et al. (1999). Their empirical model jointly determine the vehicle VMTs, fuel efficiency, and fuel prices. In addition, Greene et al. (1999) add the VMTs from the other vehicle(s) to explain a vehicle's travel behavior in order to account for the effects of the other vehicle(s)'s fuel efficiency. The current paper will interpret the introduction of other vehicle(s)' VMTs as controlling for the vehicle substitution effect between multiple household vehicles.

The data used by the current study are from the 2009 National Household Travel Survey (NHTS), which contains the most recent information related to the US household travel behavior. This dataset will enable us to provide an updated estimate of the rebound effect that will take into account the changes in household travel patterns. For example, the production share of sports utility vehicles (SUVs) increased from less than 2 percent to nearly 30 percent over 1975 to 2012, and the share of cars decreased from 71 to 50 percent.[4] Moreover, the 2009 NHTS provides an advantage because it includes household geographic variables, which as Greene et al. (1999) argue, should be included to explain VMTs but were

[3] The number is obtained by summarizing the data from the 2009 NHTS; also see Table 2.

[4] Source: US EPA, Light-duty automotive technology, carbon dioxide emissions, and fuel economy trends: 1975 through 2012. March, 2013

not available for their study.

In order to implement the analysis, the 2009 NHTS dataset is divided into four subdatasets according to the vehicle ownership level, i.e., 1-, 2-, 3-, and 4-vehicle households. Empirically, the current paper finds that without taking into the endogeneity of fuel efficiency, the Ordinary Least Squares (OLS) estimation method provides an unreliable estimate of the rebound effect: a 10 percent improvement in fuel efficiency corresponds to an increase in VMTs of over 17 percent. Meanwhile, the VMTs from different household vehicles are found to be positively correlated. This finding contradicts to the common observation that if one vehicle is used more, the other vehicles within the same household will be driven less.

Based on a system of simultaneous equations, the current paper demonstrates that the substitution effect exists for 1-, 2-, 3-, and 4-vehicle households. Using 2-vehicle households as an example, a 10 percent increase in one vehicle's VMTs would cause a decrease in the other vehicle's VMTs by 1.6 percent. More importantly, the VMT elasticity of fuel efficiency is statistically insignificant for 1- to 4-vehicle households. Therefore, the current paper finds no evidence of the rebound effect and concludes that the potential negative effect resulting from fuel efficiency improvement should not be a concern.

In contrast, Greene et al. (1999) find that the rebound effect is significant regardless of the number of household vehicles. The difference in the significance of the rebound effect might be because the current study does not assume that the elasticity of VMTs with respect to fuel efficiency has the same magnitude, but the opposite sign, as that of VMTs with respect to fuel prices. As a vehicle ages, its fuel efficiency tends to drop. However, the drop in fuel efficiency is much less observable relative to fuel price changes, so it is reasonable for households to respond more sensitively to the changes in fuel prices. Hence, the current study does not make this assumption and finds that fuel prices have a greater impact on VMTs.

The rest of the paper is organized as follows. Section 2 presents the background on the fuel efficiency rebound effect and reviews the related literature. Section 3 describes the data and model, and then Section 4 provides the estimation results. Section 5 contains the conclusion of the paper.

3.2 Background

Frondel et al. (2007) attribute the diverse magnitudes of the rebound effect reported in the literature to the different elasticities used to measure the effect. According to Sorrell et al. (2009), these elasticities can be expressed as

- $\eta_e(F)$: the elasticity of fuel consumption (F) with respect to fuel efficiency(e),
- $\eta_e(M)$: the elasticity of travel demand (M) with respect to fuel efficiency(e),
- $\eta_{P_M}(M)$: the elasticity of travel demand (M) with respect to the price of per-mile driving (P_M),
- $\eta_{P_F}(M)$: the elasticity of travel demand (M) with respect to the fuel price (P_F), and
- $\eta_{P_F}(F)$: the elasticity of travel demand (M) with respect to the fuel price (P_F).

$\eta_e(M)$ is a commonly used measure of the rebound effect Sorrell et al. (2009). The connection between the different elasticity measures can be derived as $\eta_e(F) = \eta_e(M) - 1 = -\eta_{P_M}(M) - 1$, based on the relationship $M \equiv e \cdot F$ and $P_M \equiv P_F/e$.[5] [6] Hence, if $\eta_e(M) = 0$, then $\eta_e(F) = -1$, so that if the travel demand does not change even though an efficiency improvement

[5] $$\begin{cases} M \equiv e \cdot F \rightarrow \frac{dF}{de} = \frac{1}{e} \cdot \frac{dM}{de} - \frac{F}{e} \\ \eta_e(F) = \frac{e}{F} \cdot \frac{dF}{de} \\ \eta_e(M) = \frac{e}{M} \cdot \frac{dM}{de} \end{cases} \Longrightarrow \eta_e(F) = \frac{e}{e \cdot F} \cdot \frac{dM}{de} - 1 = -1 + \eta_e(M) \text{ and}$$

$$\begin{cases} P_M \equiv \frac{P_F}{e} \rightarrow dP_M = -\frac{P_F}{e^2} \cdot de \\ \eta_{P_M}(M) = \frac{dM}{dP_M} \cdot \frac{P_M}{M} \\ \eta_e(M) = \frac{e}{M} \cdot \frac{dM}{de} \end{cases} \Longrightarrow \eta_{P_M}(M) = -\frac{dM}{de} \cdot \frac{e^2}{P_F} \cdot \frac{P_M}{M} = -\frac{dM}{de} \cdot \frac{e}{M} \cdot \frac{e \cdot P_M}{P_F} = -\eta_e(M)$$

$$\Longrightarrow \eta_e(F) = -1 - \eta_{P_M}(M).$$

[6] For more information on the relationship between the different elasticities, see Sorrell and Dimitropoulos (2008) and Greene et al. (1999).

occurs, then a 10 percent efficiency improvement, for example, will lead to a 10 percent fuel saving, or a fully achieved fuel saving.

In a more general case, $\eta_e(M) > 0$ and $-1 < \eta_e(F) < 0$ are observed, implying that fuel saving is only partially realized from a fuel efficiency improvement. For example, if a household responds to a 10 percent increase in fuel efficiency by driving an additional 4 percent, then $\eta_e(M) = 0.4$ and $\eta_e(F) = -0.6$. Thus, 6 percent of the fuel consumption will be saved, but 4 percent is taken back. In an unfavorable case, $\eta_e(M) > 1$ and $\eta_e(F) > 0$, indicating that the fuel consumption increases as result of the efficiency increase, and a backfire occurs.

Furthermore, $\eta_{P_M}(M)$, $\eta_{P_F}(M)$, and $\eta_{P_F}(F)$ are three price elasticities and their negative values can be used as an approximation of $\eta_e(M)$ to measure the rebound effect under certain circumstances Sorrell and Dimitropoulos (2008). In addition, $|\eta_{P_F}(M)| \leq |\eta_{P_M}(M)| \leq |\eta_{P_F}(F)| \leq |\eta_{P_M}(F)|$ tend to hold Sorrell and Dimitropoulos (2007). Moreover, $\eta_{P_F}(F)$ can be taken as an upper bound for the rebound effect Sorrell and Dimitropoulos (2007), and if fuel efficiency e is constant, $\eta_{P_F}(F) = \eta_{P_M}(M)$ Frondel et al. (2007).[7] In practice, which elasticity definition is used depends partly on data availability Sorrell et al. (2009).

As well as adopting different measures of the rebound effect, the related literature also uses a variety of datasets. Some studies use aggregate level data, say, national or state-level data. Sorrell et al. (2009) review 17 related studies. Among them the aggregate studies provide more consistent estimates of the rebound effect as ranging between 5 percent to 30 percent. In contrast, the dissaggregate studies based on household-level data present more diverse findings on the rebound effect, with the estimates ranging between 0 percent to 87 percent.

[7]

$$\begin{cases} \eta_{P_F}(F) = \frac{dF}{dP_F} \cdot \frac{P_F}{F} \\ P_M \equiv \frac{P_F}{e} \rightarrow dP_M = \frac{dP_F}{e} \\ M = e \cdot F \rightarrow dM = e \cdot dF \end{cases} \Longrightarrow \eta_{P_F}(F) = \frac{dM}{dP_M} \cdot \frac{1}{e^2} \cdot \frac{P_F}{F} = \frac{dM}{dP_M} \cdot \frac{P_M}{M} = \eta_{P_M}(M)$$

Greene et al. (1999) provide a possible explanation for why the estimates from aggregate data are less divergent. The substantial fuel price fluctuations since 1973 coincide with the dramatic increase in vehicle fuel economy. This coincidence creates such a well-designed experiment that the estimated rebound effect is not sensitive to alternative model specifications and research methodologies. In addition, the current paper argues that aggregate data studies tend to have less variables to control for in order to explain travel behavior, and that data aggregation may also cause less variations in the controlled variables. This argument may also explain the convergence of the results from aggregate studies.

Furthermore, whether or not (or how to) consider the potential sources of estimation bias when identifying the rebound effect could also have an impact on the empirical results. Sorrell et al. (2009) present these sources as follows: first, it is commonly assumed that households respond to an efficiency improvement in the same way as to a fuel price drop (e.g., Small and Dender (2007)). Second, in most empirical studies fuel efficiency is assumed to be exogenous. In practice, the first condition may not be satisfied because a change in vehicle fuel efficiency causes other capital costs from, for example, purchasing a new vehicle, while a change in fuel price does not induce any other costs. As a result, the use of price elasticities could result in overestimating the rebound effect because the additional capital costs spent on improving fuel efficiency are normally not available to researchers and thus not controlled for Henly et al. (1988).

Sorrell et al. (2009) also argue that price elasticities are likely not to be symmetric with the changes in energy prices. In general, the elasticities are higher during an increase in energy prices, and studies using the data with rising energy prices might overestimate the rebound effect. In addition, the current paper argues that the price elasticities tend to be greater than the efficiency elasticities because the changes in energy prices are more noticeable than those in fuel efficiency. The fuel efficiency of a vehicle generally falls over a long period, so a consumer may not observe that process in a short period. However, a consumer can notice the changes in fuel prices immediately. Hence, it is reasonable to assume that a consumer responds more to a change in fuel price.

The assumption of exogenous efficiency may not be appropriate for two reasons. First, Linn (2013) argues that vehicle fuel efficiency is likely correlated with other vehicle attributes, such as engine power or quality, which take effects on VMTs but often are excluded. Thus, the potential endogeneity of fuel efficiency might occur. Second, the potential dual causality between fuel efficiency and travel demand could also lead to the endogeneity problem. Fuel efficiency significantly affects the household travel demand. In turn, travel demand also affects on vehicle fuel efficiency. A household expecting to drive more will purchase a more fuel efficient vehicle, which will give this household a lower driving cost. The current paper will call this phenomenon the vehicle self-selection mechanism.

Particularly, the vehicle self-selection effect is not well addressed in many empirical studies, especially the earlier aggregate studies, because they use the OLS regression method to obtain the estimates of the rebound effect; for example, see Greene (1992). In contrast, the recent aggregate studies tend to recognize the interdependence of the fuel efficiency and travel demand (e.g., Small and Dender (2007)). Many empirical disaggregate studies can be found to account for the dual causality between the fuel efficiency and VMTs. Discrete/continuous or simultaneous regression equations are estimated to control for the causality (for example, see Goldberg (1998), Greene et al. (1999), and West (2004)). However, even these studies still present diverse estimates of the rebound effect.

Furthermore, the rebound literature often ignores the interdependence between multiple vehicles in a household. Some studies may aggregate all vehicle miles by household or just choose a single-vehicle household to investigate (e.g., Frondel et al. (2007)). Greene et al. (1999) state that the different vehicles in a household are most likely to have quality differences, and that the characteristics of the other vehicles will affect each vehicle's use. Hence, aggregating the VMTs of all household vehicles would ignore the interactions between vehicles. An increase in one vehicle's VMTs induced by a fuel efficiency improvement would decrease the use of the other household vehicle(s). As a result, treating household vehicles independently may result in overestimating the rebound effect. The current paper interprets the interaction among household vehicles as a vehicle substitution effect.

Greene et al. (1999) present the most careful investigation of the direct rebound effect Sorrell et al. (2009) by building up a system of simultaneous equations in which VMTs, fuel efficiency, and fuel prices are treated as endogenous variables. Greene et al. (1999)'s econometric model uses VMTs to explain a vehicle's fuel efficiency and controls for vehicle interaction by including the VMTs of other vehicles as explanatory variables for a particular vehicle's VMT equation.[8] They estimate a direct rebound effect of +0.2.

Although following Greene et al. (1999)'s proposed framework, the current study finds that the rebound effect is not statistically significant across vehicle ownership. The contradiction in conclusion can be explained by the fact that the current study does not assume that VMTs respond in the same way to an equivalent change (but opposite) in fuel efficiency and fuel price. In addition, the dataset used by this paper contains the geographical variables, measured by housing densities at a block level, which are not available to Greene et al. (1999).

A recent study by Linn (2013) to investigate the rebound effect is also closely related to the current paper. Linn (2013) introduces the mean fuel efficiency of a household's other vehicles into VMT&fuel efficiency equation to control for the interaction between household vehicles. He also does not impose any restriction on the coefficient estimates of fuel efficiency and fuel prices on VMTs. Lastly, he states that the problem of omitted variables is the major source that biases the estimated effect of fuel efficiency. To control for the omitted variables, he accounts for vehicle model fixed effects and instruments the vehicle's fuel efficiency by the interactions of the fixed effects with the gasoline price at the time when a household purchases its vehicle. However, he does not directly address the issue of vehicle self-selection and finds a significant rebound effect, ranging between 0.2 to 0.4 percent.

[8] Greene et al. (1999) do not incorporate the characteristics of all other household vehicles to examine each vehicle's own use because doing so would make the system of equations to be insolvable.

In contrast, the current paper takes the self-selection issue as a more severe problem that biases the empirical results of the rebound effect. Simultaneously regressing VMTs and fuel efficiency is used by the current study to correct the bias, and meanwhile, the problem caused by the omitted vehicle attributes is mitigated by adding vehicle age, category, and fuel types into our regression model. Emphasizing different sources that cause the issue of fuel efficiency endogeneity and adopting different estimation techniques may explain the difference in conclusion between this study and Linn (2013). In addition, the vehicle model fixed effects used by Linn (2013) will absorb a significant portion of the variation of fuel efficiency, which may also take effects on the estimation of the rebound effect.

Last but not least, some studies also adopt quasi-experimental approach to identify the rebound effect, based on energy consumption induced by energy service before and after an energy efficiency improvement. The quasi-experimental approach is most adopted to examine the change in energy demand by household heating, for example, following the installation of a more fuel efficient boiler (for a review of the related studies, also see Sorrell et al., 2009).

A recent study by West et al. (2014) also uses the quasi-experimental approach to determine the rebound effect induced by fuel efficiency improvement. These researchers state that the Cash for Clunkers (CARS) program results in a credibly exogenous "policy-induced improvement" in fuel efficiency. They find that the new vehicles' owners who are barely eligible to participate in the CARS program do not drive more miles than the barely ineligible new car buyers for one year after the CARS transaction, though the formers purchase 4 to 6 percent higher efficiency vehicles. They conclude that the rebound effect is likely to be insignificant. This conclusion is consistent with ours.

To identify the direct rebound effect, the current paper uses one of the most recent datasets collecting information on the US household travel behavior. As argued earlier, the vehicle ownership and use pattern of US households have changed dramatically. The use of the 2009 NHTS will incorporate these changes to investigate the relationship between fuel efficiency and VMTs. In the following sections, the 2009 NHTS dataset and estimation method will be described.

3.3 Methodology

Data and model

The data for this study are from the 2009 NHTS and were collected by the U.S. Federal Highway Administration (FHWA). The 2009 NHTS' predecessor is not used because of its inconsistency in data collection, especially in the approach for estimating VMTs.[9] The NHTS collects travel information, through telephone survey, from the the U.S. households with landline, while the telephone numbers for these households are required to be residential. The survey respondent has to be an adult (at least 18 years old) household member. The NHTS is a list-assisted random digit dialing (RDD) telephone number survey such that households with landline telephones have an equal probability to be interviewed. The response rate is 25.1 percent.

The 2009 NHTS dataset provides information on household characteristics, geographical variables, and vehicle attributes (including VMTs), which enables us to quantify household travel behavior and understand transportation patterns.[10] The annual VMTs for the 2009 NHTS vehicles are estimated based on three key factors: single odometer readings, self-reported VMTs, and miles driven during the designated sample day. The survey contains 150,147 households and 309,163 sample vehicles for the 50 US states and the District of Columbia. In the following paragraphs, the empirical methodology used in the current study is first introduced, and the variables used in the empirical model are described in detail.

[9] Annual VMTs from the 2001 NHTS are derived from two odometer readings, while only a single odometer reading is available in the 2009 NHTS, and VMTs are obtained from this single reading and other available information.

[10] The 2009 NHTS also collects the information on daily trips, e.g., trip purpose, mode of transportation used, and how long a trip takes. This information can be found in a travel day trip file. However, due to the purpose of the current study, it does not use this file.

Greene et al. (1999) state that vehicle travel can be regarded as one of household-produced services and has both quantity and quality components. The quality components should not be ignored because the same number of miles driven by an old sedan or a new luxury car have qualitative differences because these vehicles are distinguished by vehicle attributes such as safety, comfort, and maneuverability. Therefore, simply aggregating all vehicles' VMTs within each household may not be appropriate for quantifying household travel behavior. Greene et al. (1999) propose that only the VMTs of other household vehicles but not their characteristics should be included to explain the use of a particular vehicle, and present the travel demands in a three-vehicle household as follows:

$$\begin{aligned} M_1 &= a_1V_1 + f_1H + g_1C_1 + b_{12}M_2 + b_{13}M_3 \\ M_2 &= a_2V_2 + f_2H + g_2C_2 + b_{21}M_1 + b_{23}M_3 \\ M_3 &= a_3V_3 + f_3H + g_3C_3 + b_{31}M_1 + b_{32}M_2, \end{aligned} \tag{3.1}$$

where M_i is the VMTs for vehicle i, V_i is an attribute vector of vehicle i, C_i is the total cost per mile for vehicle i, and H is a vector containing the household characteristics.[11] The cost of driving a mile (C_i) is computed as the sum of the fuel cost $\left(\frac{P_{F_i}}{mpg_i}\right)$, other operation costs (OC_i), and depreciation (δ_i), mathematically expressed as $C_i = \frac{P_{F_i}}{mpg_i} + OC_i + \delta_i$.

Furthermore, a system of equations for vehicle one in the three-vehicle households is presented as

$$\begin{cases} M_1 = a_{11}V_{11} + f_{11}H + g_{11}\left(\frac{P_{F_1}}{mpg_1}\right) + b_{12}M_2 + b_{13}M_3 \\ mpg_1 = a_{12}V_{12} + f_{12}H + g_{12}M_1 + d_{12}P_{F_1}. \end{cases} \tag{3.2}$$

[11]The VMTs from the other two household vehicles can not combined into one variable, i.e., the VMTs of all other vehicles because the VMT of each individual vehicle is endogenous and the summing up will forcely destroy the endogeneity nature the VMT variables.

A household expecting to drive more will choose to own more efficient vehicles. Now, *mpg* is treated as endogenous in the system. In addition, the VMTs of the other two vehicles are assumed to directly affect the VMTs and indirectly affect the fuel efficiency of the vehicle of interest, through their impacts on its use. Due to the interactions between all three vehicles within the same household, **six** equations (two for each vehicles) are jointly estimated.

The above simultaneous system above is used here because it accounts for both the vehicle self-selection and substitution effects, while keeping the estimation of such a system tractable. In addition, the operation cost and depreciation normally are not available to household travel surveys (including the 2009 NHTS), and the estimated rebound effect could be biased if these omitted variables are correlated with the variables contained in the regression. A system that incorporates miles, cost, and MPG as endogenous could minimize the estimation bias Greene et al. (1999).

Unlike Greene et al. (1999), the current study does not consider the fuel prices paid by households as endogenous. Fuel prices are affected mainly by factors such as world oil price fluctuations, fuel transportation costs, and fuel taxes, and households are likely to have little power to determine fuel prices. The prices also tend to exhibit less variations in a cross-sectional dataset compared with time-series data.

In order to explicitly present the rebound effect, only the continuous variables of system (2) are used in a natural logarithm, which becomes

$$\begin{cases} Lm_1 = a_0 + a_1 Lvehage_1 + a_2 Lp_F + a_3 Lmpg_1 + a_4 Lincome + a_5 Lhhsize + a_6 Lresdn \\ \qquad + a_7 Lwrkcount + a_7 Auto + a_8 Van + a_9 SUV + a_{10} Homeown + a_{13} Urban\_indic \\ \qquad + a_{14} Rail\_indic + a_{11} Adltnochild + a_{12} Adltchildd_1 + \gamma Race + d_1 Lm_2 + d_2 Lm_3 \\ Lmpg_1 = b_0 + b_1 Lm_1 + b_2 Lp_F + b_3 Lincome + b_4 Lresdn + b_5 Lvehage_1 + b_6 Auto \\ \qquad + b_7 Van + b_8 SUV + b_9 Gasoline + b_{10} Diesel + b_{11} Ntrlgas. \end{cases} \tag{3.3}$$

Table Tab. 3.1 describes the variables used in the system (3), which are, intuitively, important for explaining household travel behavior. A vehicle is likely to be driven less as it ages ($Lvehage$) and to perform worse over time. Households with higher income levels ($Lincome$) drive more if travel service can be regarded as a normal good. It is not surprising that a household with more family members ($Lhhsize$) will have higher travel demand. A household with more workers ($Lwrkcount$) tend to have more driving. In addition, household life-cycle variables may also affect VMTs: retired adults with no children have no need to go to work or to take their children to school, and thus drive less compared to unretired adults either with no children ($Adltnochild$) or with children ($Adltchild$). A vector of 7 race dummies ($Race$) is also used to explain travel demand.

The relationship between land use density, measured by housing units per square mile at a block level ($Lresdn$) and vehicle use has been extensively examined in the urban economics literature. For example, Brownstone and Golob (2009) argue that in a denser area, accessing places of employment and other destinations like shopping malls is easier than in other areas, so a household living in a denser area will drive less. Similarly, a household located in an urbanized area ($Urban\_indic$) or in an area with rails ($Rail\_indic$) may also have less demand to drive. This study also examines whether a household owns a housing place ($Homeown$) or rents it could affect VMTs. Lastly, vehicle-type dummies are also included to explain VMTs.

The other endogenous variable, fuel efficiency, is determined mainly by vehicle type, age, fuel type, fuel price, and household characteristics. Households with high income levels can afford more luxury and larger-size vehicles, which tend to have lower fuel efficiency. Housing densities also affect the efficiency through the impacts on a household's vehicle choices because maneuvering and parking a smaller vehicle in a high-density area is easier than maneuvering and parking a larger vehicle Brownstone and Golob (2009). Hence, residential density is likely to be positively correlated with fuel efficiency. A household with a bigger size is likely to own a larger vehicle which, generally, is less fuel efficient.

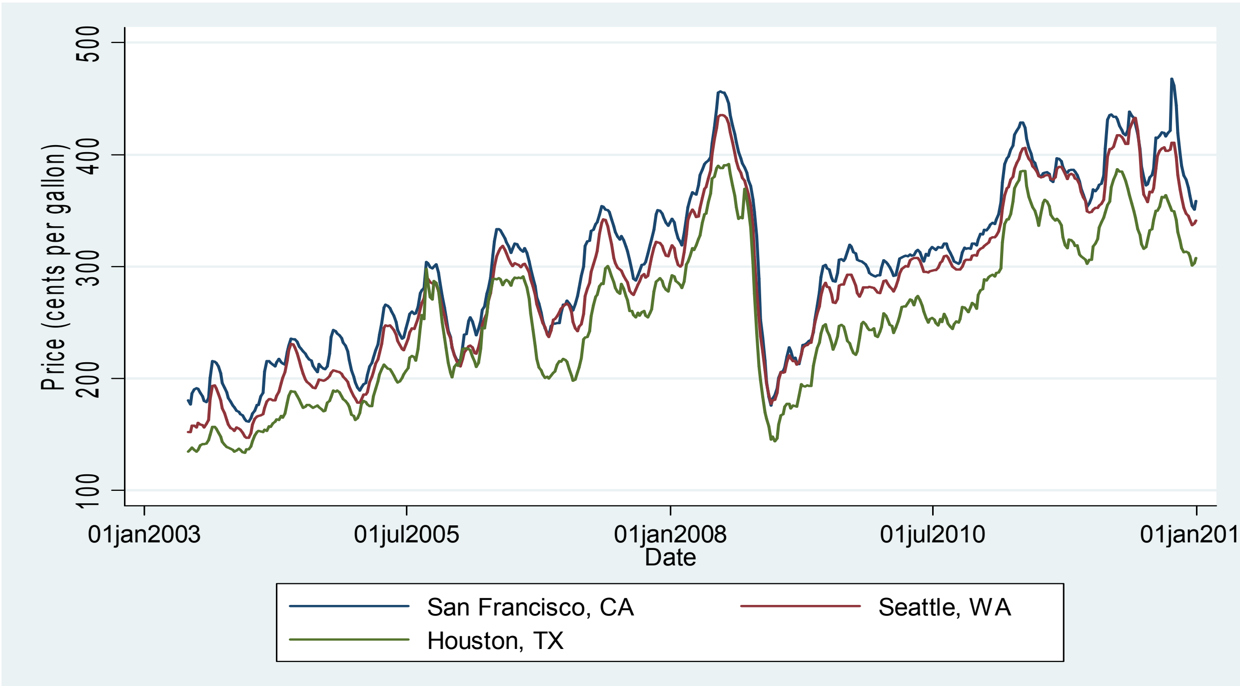
In addition, the fuel prices when or before households plan to buy a vehicle could affect their vehicle choices and thus fuel efficiency. As a result, the current fuel price Lp_F seems to be unrelated to the efficiency. Lp_F in the 2009 NHTS are collected by the U.S. Energy Information Administration (EIA). These prices are monthly retail prices at the Petroleum Administration for Defense Districts (PADD) level. However, the current price could be a representation of the historical fuel prices. Thus, if an area is observed to have a high current fuel price, the past fuel prices in this area are likely to have also been high relative to those in other areas. The households in such an area are more likely than those in other areas to choose more fuel efficient vehicles.

The United States can be partitioned into five Petroleum Administration for Defense Districts (PADD). The U.S. EIA provides the retail gasoline prices (regular-all formulations) for ten representative cities in the different PAD Districts.[12] San Francisco, CA has the highest mean of weekly gasoline prices, followed by Los Angeles, CA and Seattle, WA, among the ten cities over the period from June, 2003 to December, 2012, while Houston, TX has the lowest mean. The gasoline prices for three cities are presented in Figure Fig. 3.1, which reveals that the past fuel prices are consistently higher in an area which has relatively higher current fuel prices compared to other areas.[13] Therefore, the current fuel price is expected to be positively associated with fuel efficiency because a high fuel price leads to a high driving cost. Moreover, the similar changing pattern of fuel prices across the three cities also provides some evidence that the prices are most likely to be exogenous to households.

[12] The ten cities and associated districts are Boston (MA), Miami (FL), and New York City (NY) from PAD District 1; Chicago (IL) and Cleveland (OH) from PAD District 2; Houston (TX) from PAD District 3; Denver (CO) from PAD District 4; and Los Angeles (CA), San Francisco (CA), and Seattle (WA) from PAD District 5.

[13] San Francisco, CA and Los Angeles, CA are from the same district (PAD District 5), and these two cities have highly similar fuel prices. Los Angeles is not included in this figure.

Figure 3.1: Gasoline retail prices from June, 2003 to December, 2012



Data structure

Based on the set-up of the empirical model, this study divides the 2009 NHTS data into four sub-datasets: 1-, 2-, 3-, and 4-vehicle households.[14] The term "vehicle" here refers to an automobile, van, SUV, or truck rather than a recreational vehicle (RV), motorcycle, or golf cart because replacing the former with the latter is difficult in terms of functionality. Moreover, some criteria have to be used to purify the household vehicles because important information, such as vehicle type and vehicle age, might be lacking for one or more vehicles. In addition, some vehicles may be outliers in the sense that they are either rarely used or driven too much. They are identified if the annual fuel consumption of a vehicle is less than 25 or over 6,000 gallons.[15] Due to the interaction between household vehicles, households with vehicles that are either rarely used or driven too much are excluded from the current study. After purification, the four sub-datasets are determined according to the number of

[14] Due to the small percentage of households owning five or more vehicles (just over 2 percent) and the issue of missing data, these households are excluded from the current study.

[15] A similar screening criterion was used by Greene et al. (1999).

“purified” household vehicles

More details need to be introduced to construct the sub-datasets. In the sub-dataset of 4-vehicle households, for example, each household has four records. Every record for a particular 4-vehicle household has all household characteristics and four vehicles and their attributes. All household-related variables appear in the same positions across the four records, while each vehicle is included in each record once and only once. The sequence of vehicles could be 1, 2, 3, 4 in the first record, 2, 3, 4, 1 in the second, 3, 4, 1, 2 in the second, and 4, 1, 2, 3 in the last record. Accordingly, the other four sub-datasets can be constructed.

Table Tab. 3.2 below presents the summary statistics for the related continuous variables, according to household vehicle ownership level.[16] Regardless of whether the purification process is applied or not, 2-vehicle households occupy the highest proportion among all households, followed by 1-, 3-, and 4-vehicle households. Moreover, approximately 70 percent of the households own more than one vehicle, and hence investigating the travel demand for multiple vehicles is crucial in order to understand the travel behavior of the US households. After purification, the proportions for 3-, and 4-vehicle households decrease mainly because the missing key vehicle variables are more likely to occur as vehicle ownership level rises.

Regarding travel demand, the average VMTs are close for households with two or more vehicles (around 11,600 miles per vehicle, annually), while 1-vehicle households drive relatively less (around 9,803 miles). Not surprisingly, the vehicle ownership level and household income increase with household size. Moreover, the mean fuel efficiency tends to fall as households own more vehicles, while the mean vehicle age tends to rise.

[16] The weight of households with six or more vehicles before purification is only 0.65%. This household category is ignored in this study.

“Partial” versus “system” elasticity

Regarding the system (3), the estimate of a_3 would be interpreted as a “partial” rebound effect because this estimate only measures only the response of a vehicle with improved fuel efficiency. The estimate of a_3 is not restricted to be equal to that of a_2; i.e., because of the argument made earlier in this paper, households are assumed to not necessarily respond in the same way to an equivalent change in fuel price or fuel efficiency. In addition, for multiple-vehicle households, an increase in fuel efficiency for one household vehicle will lead to more utilization of this vehicle, and this increased use might reduce the use of the other vehicles. As a result, the “system” MPG elasticity would be also dependent on, but lower than, the “partial” rebound effect, a_3.

The relationship between the “partial” and “system” effects can be illustrated by using 3-vehicle households as an example. First, combine system (3) with the other two sets of six equations for vehicles two and three, and then the VMTs for three vehicles from a household can be solved and approximated as

$$\begin{cases} M_1 = K_1 + M_2^{\pi_1} \\ M_2 = K_2 + M_1^{\pi_2} \\ M_3 = K_3 + M_1^{\pi_3}, \end{cases} \tag{3.4}$$

where K_1, K_2, and K_3 are all constant terms. Starting with a 1 percent rise in the fuel efficiency of vehicle one, the rise would cause M_1 to increase, initially, by a_3 percent. M_2 and M_3 will increase by $a_3\pi_2$ and $a_3\pi_3$ percent, respectively, according to the last two equations in the system (4). This increase, in turn, affects M_1 and triggers another round of VMT changes. This iteration will continue infinitely. Provided that $|\pi_1\pi_2| < 1$, the ultimate VMT changes (*in percentage terms*) induced by the 1 percent improvement of fuel efficiency for vehicle one can be expressed as

$$\begin{cases} \triangle M_1 = a_3 + a_3\pi_1\pi_2 + a_3(\pi_1\pi_2)^2 + \cdots = \frac{a_3}{1-\pi_1\pi_2} \\ \triangle M_2 = a_3\pi_2 + a_3(\pi_1\pi_2)\pi_2 + a_3(\pi_1\pi_2)^2\pi_2 + \cdots = \frac{a_3\pi_2}{1-\pi_1\pi_2} \\ \triangle M_3 = a_3\pi_3 + a_3(\pi_1\pi_2)\pi_3 + a_3(\pi_1\pi_2)^2\pi_3 + \cdots = \frac{a_3\pi_3}{1-\pi_1\pi_2}. \end{cases} \tag{3.5}$$

Taking into account the responses from all three vehicles, the system elasticity can be calculated as $\left(\frac{1+\pi_2+\pi_3}{1-\pi_1\pi_2}\right)a_3$.[17] The coefficients $\pi_1 - \pi_3$ are connected to those in system (3) according to the relationship $\pi_1 = d_1$, $\pi_2 = d_2$, and $\pi_3 = d_1$, while the last two equalities can be inferred from the special data structure for the current study.

3.4 Results

One-vehicle households

Table 3 provides the coefficient estimates according to the household vehicle ownership level. For 1-vehicle households, the VMT elasticity with respect to the household income level is 0.132, indicating that a household with a \$40,000 income will drive 13.2 percent more than one with a \$20,000 income. Household size also significantly affects VMTs, with an elasticity of 0.149, indicating a 2-member household will have 14.9 percent more travel demand compared to a 1-member household, given one vehicle is owned. Because the elasticity of residential density is only 0.047, it appears to have a small effect on VMTs. However, this estimate means that a household moving its housing location from an area with 1000 housing units per square mile to one with 2000 housing units would decrease its driving by 4.7 percent. In addition, the table shows that a 2-worker household would drive 7.1 percent

[17]The approach used to derive the system elasticity can be applied to the cases with different vehicle ownership levels. The derivation for 1- and 2-vehicle households can be obtained in Greene et al. (1999).

more than 1-worker household.

The race of household suvery respondent does not significantly affect driving demand. However, the household life cycle affects the VMTs. Unretired adults with (or without) children will travel 2147 (or 1272) miles more than retired adults without children, annually, if the latter are assumed to drive 9803.3 miles−the mean travel demand of 1-vehicle households (see Table Tab. 3.2). Moreover, a household drives less if its housing unit is owned or located in an urban area, by 0.048 or 0.027 in natural logarithm terms, which converts into 482 or 268 miles according to the mean miles for one-vehicle households. A household locating in an area with rail would drive 158 miles less.

Vehicle attributes are also important for calculating the rebound effect. The VMT elasticity with respect to vehicle age is estimated as -0.113. This result indicates that an 11-year-old vehicle is driven by 1.13 percent less than a 10-year-old vehicle because the former increases in age by 10 percent. In addition, for 1-vehicle households, the use of automobile, vans, or SUVs is not significantly different from that of trucks (a dummy variable omitted in the regression). More importantly, a vehicle will be used 4.7 percent less if the fuel price increases by 10 percent. For the measure of the rebound effect, $\eta_e(M)$, the estimated elasticity is 0.116, which is not statistically significant.

The other endogenous variable in the system is fuel efficiency. The household income level and its residential density have significant effects on MPG, although the empirical estimates of the two effects are small. Doubling the household income (or housing density) would result in a 0.8 percent reduction (or a 0.6 percent rise) in MPG. Moreover, vehicle attributes including vehicle age and type also significantly affect MPG. For example, the fuel efficiency of an 11-year-old vehicle would depreciate by 0.64 percent relative to a 10-year-old vehicle. Table 3 reveals that automobiles on average have the highest MPG, followed by vans, SUVs, and trucks. In addition, a vehicle with gasoline, diesel, or natural gas has a much lower MPG than an electricity-powered one (a dummy variable omitted in the system).

Particularly, the Table 3 illustrates that the causal relationship between VMTs and fuel efficiency is found to be significantly positive in the MPG equation. An increase in VMTs by 10 percent would lead to an increase in fuel efficiency by 1.5 percent, suggesting that households do take into account their expected travel demand when choosing their vehicles. Without controlling for the endogeneity of fuel efficiency, the rebound effect would become too high. It is estimated as 1.96 by the OLS estimation method (see Table Tab. 3.4).

Multiple-vehicle households

When a household owns multiple vehicles, the system of equations to be estimated becomes slightly different than the one used for 1-vehicle households. For example, when 2-vehicle households are used , the number of simultaneous equations is four, with two equations for each household vehicle. Second, the VMTs for the other vehicle are introduced into the right-hand side of the VMT equation for each vehicle, so that two vehicles from the same household appear twice in the 2-vehicle sub-dataset. In the first round, the VMTs of vehicle one are a dependent variable while the VMTs of vehicle two are an explanatory variable. In the second round, the vehicles one and two in the previous round are listed as vehicles two and one, respectively. Due to the two vehicles' interchange of roles, the coefficient estimates for vehicle one will be identical to those for vehicle two. Moreover, this inference can be generalized and applied to the households owning three or more vehicles. As a result, only the regression results for vehicle one will be provided in the rest of this paper.

Table 3 also presents the coefficient estimates of the VMT equation for multiple-vehicle households. The estimated income elasticities are 0.09, 0.07 and 0.02 for 2-, 3-, and 4-vehicle households, respectively. The effects of household income on travel demand exhibit a decreasing trend as the number of household vehicles increases. Household size is shown to have a significant impact on VMTs. Doubling the household size could lead to around 17.3 to 19.6 percent additional miles. Residential density has a relatively stable effect on VMTs, and doubling the density would decrease VMTs by approximately 4 to 6 percent.

A 2- or 3-vehicle household living in its owned housing unit tends to drive less than one living in a rented unit, while owning or renting does not affect the travel demand of the households with four vehicles. Similarly, $Urban\_indic$ and $Rail\_indic$ affect only 2- and 3-vehicle households, and living in an urban area and (or) an area with rails would cause these households to drive less. Similar to 1-vehicle households, unretired adults with (or without) children have a higher travel demand than retired adults without children because the former need to drive to work and (or) drive their children to school. Race variables do not have a consistent impact on VMT.

Moreover, vehicle age affects multiple-vehicle households' travel more than 1-vehicle households, and doubling the vehicle age will reduce the travel demand from 15.6 percent to 24.1 percent. Fuel prices also significantly affect household travel behavior. A fuel price rising by 10 percent will decrease VMTs by 3.2, 5.3, and 4.8 percent for 2-, 3-, and 4-vehicle households, respectively. In addition, automobiles are not driven differently from trucks, while vans and SUVs are driven more than trucks.

Regarding the most important estimate of the rebound effect, Table 3 shows that the magnitude of the effect is less than 0.15 and the effect is statistically insignificant across vehicle ownership. In addition, the interaction between household vehicles is shown to be important for determining the VMTs for multiple-vehicle households. For 2-, 3-, and 4-vehicle households, a 10 percent rise in the VMTs driven by other vehicles will lead to a reduction in VMTs by the vehicle of interest of approximately 1.1 to 1.8 percent, and the result is statistically significant at 1 percent significance level. Therefore, once an efficiency improvement for one household vehicle occurs, this vehicle might be used more due to its lower travel cost. Meanwhile, the driving demand for other vehicles could be reduced as shown in Table 3, and this reduction could mitigate the increase in aggregate driving demand resulting from the efficiency improvement.

In terms of the MPG equation, Table 3 shows that income plays a consistent role in determining the fuel efficiency of household vehicles, such that doubling the income leads to a decrease in fuel efficiency of 0.6 to 1.6 percent across vehicle ownership levels. Thus, households with higher incomes generally choose more fuel consuming vehicles, which are likely to provide better quality service and driving experience to these households. In addition, Table 3 shows that households in a denser area tend to drive more fuel efficient vehicles. This finding is explained by the observation that a smaller size of vehicle, normally with a higher fuel efficiency, is easy to park and maneuvered in a denser area.

Vehicle age has a significant impact on fuel efficiency, which decreases by 1.6 to 4.2 percent according to the vehicle ownership level if the vehicle age is doubled. High fuel prices are associated with high fuel efficiency. Hence, households do take into account driving cost when deciding which combination of vehicles they should buy. Vehicle body and fuel types also play an important role in determining fuel efficiency. Specifically, automobiles are the most fuel efficient, followed by vans, SUVs, and trucks. Electrical vehicles have the highest MPG, followed by gasoline powered vehicles, while diesel fuel vehicles and natural gas vehicles have similar efficiency in terms of miles per gasoline-equivalent gallon.

With respect to the multiple vehicle households, a vehicle's own miles are also shown to positively affect fuel efficiency, and a household is likely to own more efficient vehicles if it expects to have high travel demand. Hence, the vehicle selection mechanism works when a household determines its vehicle combination. For multiple vehicle households, the elasticity of MPG with respect to VMTs is estimated to be in a range of 1.7 to 2.4 percent across vehicle ownership. Without taking into account the endogeneity of fuel efficiency (or the vehicle selection effect), the estimate of the rebound effect may become unconvincing. Table Tab. 3.4 shows that the rebound effect without controlling for the potential endogeneity is estimated to be close to 2, which is far above the typical rebound effect obtained in the related literature. The OLS estimates further show that the travel demand for all household vehicles changes in the same direction, even though this finding does not make sense.

The current study adopts the empirical model used by Greene et al. (1999). However, their study empirically illustrates that the rebound effect exists across different vehicle ownership levels, even for 4- or 5-vehicle households, in which travel by other vehicles generally does not affect the VMTs of each vehicle. The divergence may occur because the current study does not make Greene et al. (1999)'s important assumption that households facing an equal change, but in the opposite direction, in fuel price and MPG will respond in the same way.

3.5 Conclusion

The United States government has imposed increasingly stringent standards on vehicle fuel economy as a policy for coping with rising energy demand and vehicle pollution from household travel. However, an improvement in fuel efficiency will lead to a decrease in travel cost and encourage households to drive additional miles. If this rebound effect were significant, it could neutralize the potential benefits that could be obtained from increasing fuel efficiency. Hence, the magnitude of the rebound effect must be empirically identified in order to determine the effectiveness of fuel economy standard requirements.

Although many researchers have investigated the relationship between fuel efficiency and travel demand, the estimates of the rebound effect tend to be inconsistent, with a range from zero to over +0.8. The divergence in the estimated effect may first lie in the differences in the measures of the rebound effect across studies. Second, the divergence may also result from the different types of data used in the literature. Aggregate studies provide a much narrower range for the rebound effect, between 10-30 percent, compared to the studies using household level data.

Moreover, whether the endogeneity of fuel efficiency (or vehicle self-selection) is controlled for or not could also cause the estimated rebound effects to be significantly different. Furthermore, the related literature can also be distinguished according to how the researchers deal with the interaction (or substitution) between multiple household vehicles, while the related studies tend to treat different vehicles from the same household independently.

The current study has attempted to identify the rebound effect. Based on the 2009 NHTS, this study finds that without controlling for the vehicle self-selection effect, the estimated rebound effect obtained by OLS becomes too high to be convincing. In addition, the OLS regression results also show that the changes in the VMTs of different household vehicles move in the same direction, even though this finding does not make economic sense.

Using the model proposed by Greene et al. (1999), which accounts for both vehicle self-selection and substitution effects at the same time, this study also demonstrates that vehicle substitution exists for 2-, 3-, and 4-vehicle households. Hence, an increase in the VMTs of one household vehicle would reduce the travel demand of the other vehicles. Moreover, the the substitution effect tends to be smaller as the number of household vehicles rises.

Furthermore, the study finds that the direct rebound effect is statistically insignificant for 1- to 4-vehicle households. This result differs from that obtained by Greene et al. (1999), who find that the rebound effect is significant regardless of the number of vehicles owned by a household. The difference may be explained by the current study's dropping the assumption that the VMT elasticity of fuel efficiency improvement is opposite but of the same magnitude to the elasticity of the fuel price. In addition, the empirical finding of the current paper is also different from that of Linn (2013), which illustrates that addressing different sources of the endogeneity of fuel efficiency could also cause the divergence in empirical results.

Some rebound literature argues that the rebound effect varies according to vehicle travel demand. For example, Su (2012) finds that those with much higher or much lower travel demand compared to average travel level tend to respond less to the change in fuel price per mile. The behavioral change with respect to VMT distribution is not investigated by the current paper. This issue will be left for the future study.

Table 3.1: Variable descriptions

Variables[1]	Definition
Continuous Variables	
Lm	Annual vehicle miles traveled.
$Lmpg$	EIA derived miles per gasoline-equivalent gallon estimate.
Lp_F	EIA monthly gasoline retail prices at a PADD level (dollars per gallon).
$Lvehage$	Vehicle age (2009 minus model year)[2].
$Lincome$	Household income[3].
$Lhhsize$	Count of household members.
$Lwrkcount$	Count of household workers.
$Lresdn$	Housing units per square mile-block group.
Dummy variables	
$Auto$	Vehicle is an automobile.
Van	Vehicle is a van.
SUV	Vehicle is a sport utility vehicle (SUV).
$Truck$	Vehicle is a Truck.
$Gasoline$	Fuel type is motor gasoline.
$Diesel$	Fuel type is diesel.
$Ntrlgas$	Fuel type is natural gas.
$Electricity$	Fuel type is electricity.
$Homeown$	Housing unit is owned.
$Urban\_indic$	Home address located in urbanized area.
$Rail\_indic$	Home address located in metropolitan statistical area (MSA) with rail.
$Adltnochild$[4]	Adult(s) with no children.
$Adltchild$[4]	Adult(s) with one or more children.
$Race$	A vector of 7 race dummies.

Notes: 1. All continuous variables are used in natural logarithms, which are indicated by the prefix "L". 2. A vehicle of model year 2009 is treated as a vehicle age of one. 3. HH income is calculated as the midpoints of the 18 income categories in the NHTS with $170,000 assigned for the top category and missing incomes, respectively (this number was adopted by Brownstone and Golob, 2009). 4. The 2009 NHTS has life-cycle categories as follows: one adult with no children; two or more adults with no children; one adult with the youngest child aged 0 to 5; one adult with the youngest child aged 6 to 15; one adult with the youngest child aged 16 to 21; two or more adults with the youngest child aged 0 to 5; two or more adults with the youngest child aged 6 to 15; two or more adults with the youngest child aged 16 to 21; one adult, retired, with no children; and two or more adults, retired, with no children. This paper aggregates these categories into the three categories used in the regression equation: adults with no children, adults with one or more children, and retired adults with no children.

Table 3.2: Summary statistics by household vehicle ownership level[1]

	Before purification		After purification							
n of vehicles	n of HHs	Weight	n of HHs	Weight	*m*	*mpg*	*vehage*	*income*	*hhsize*	*resdn*
One	41426	29.0%	37865	31.6%	9803.3	21.36	8.10	40064.6	1.57	2108.5
Two	65168	45.6%	57213	47.7%	11533.0	20.68	7.53	79207.0	2.53	1303.5
Three	25630	17.9%	19096	15.9%	11675	20.37	8.32	92871.6	2.95	1007.7
Four	7788	5.4%	4594	3.8%	11760.6	20.28	8.92	100315.6	3.43	856.9

Note: 1. The vehicles here are not distinguished as either automobiles, vans, SUVs, or trucks.

Table 3.3: Regression output

	1-vehicle		2-vehicle		3-vehicle		4-vehicle	
	$Lm1$	$Lmpg1$	$Lm1$	$Lmpg1$	$Lm1$	$Lmpg1$	$Lm1$	$Lmpg1$
$Lm1$		0.150***		0.199***		0.169***		0.239***
		(0.020)		(0.007)		(0.010)		(0.017)
$Lmpg1$	0.116		0.115		-0.003		0.152	
	(0.459)		(0.117)		(0.154)		(0.206)	
Lp_F1	-0.470***	0.326***	-0.322***	0.272***	-0.528***	0.191***	-0.476***	0.121***
	(0.172)	(0.035)	(0.061)	(0.015)	(0.085)	(0.021)	(0.156)	(0.037)
$Lincome1$	0.132***	-0.008**	0.092***	-0.016***	0.072***	-0.010***	0.019*	-0.006***
	(0.010)	(0.003)	(0.005)	(0.001)	(0.007)	(0.001)	(0.010)	(0.002)
$Lhhsize1$	0.149***	-0.023***	0.173***	-0.016***	0.192***	0.007**	0.196***	0.002
	(0.022)	(0.005)	(0.013)	(0.002)	(0.018)	(0.003)	(0.028)	(0.006)
$lwrkcount$	0.071**		0.145***		0.136***		0.193***	
	(0.032)		(0.009)		(0.012)		(0.021)	
$Lresdn1$	-0.047***	0.006***	-0.043***	0.006***	-0.041***	0.001**	-0.058***	0.005***
	(0.006)	(0.001)	(0.003)	(0.001)	(0.004)	(0.001)	(0.007)	(0.001)
$Homeown$	-0.048***		-0.037***		-0.064***		-0.044	
	(0.017)		(0.010)		(0.020)		(0.038)	
$Urban\_indic$	-0.027		-0.039***		-0.046***		0.007	
	(0.021)		(0.008)		(0.011)		(0.019)	
$Rail\_indic$	-0.016		-0.025***		-0.026**		0.024	
	(0.018)		(0.007)		(0.011)		(0.018)	
$White$	0.002		-0.054**		-0.021		0.135**	
	(0.056)		(0.027)		(0.041)		(0.066)	
$Black$	-0.005		-0.064**		-0.017		0.067	
	(0.059)		(0.030)		(0.044)		(0.071)	
$Asian$	-0.108		-0.068**		-0.138***		0.228***	
	(0.071)		(0.030)		(0.047)		(0.077)	
$Indian$	0.100		-0.072*		-0.001		0.047	
	(0.091)		(0.042)		(0.062)		(0.092)	
$Hawaiian$	-0.044		-0.033		0.098		0.075	
	(0.119)		(0.052)		(0.090)		(0.118)	
$Hispanic$	0.030		-0.052*		-0.082*		0.166**	

	(0.064)		(0.031)		(0.048)		(0.078)	
Multiracial	0.148		-0.011		0.052		0.332***	
	(0.091)		(0.044)		(0.066)		(0.105)	
Adltnochild	0.122***		0.171***		0.138***		0.109***	
	(0.022)		(0.009)		(0.013)		(0.022)	
Adltchild	0.198***		0.209***		0.181***		0.147***	
	(0.029)		(0.012)		(0.015)		(0.023)	
*Lvehage*1	-0.113***	-0.064***	-0.156***	-0.042***	-0.218***	-0.042***	-0.241***	-0.016***
	(0.039)	(0.003)	(0.009)	(0.001)	(0.013)	(0.002)	(0.018)	(0.005)
*Auto*1	-0.132	0.351***	-0.026	0.354***	0.050	0.348***	-0.028	0.334***
	(0.156)	(0.006)	(0.043)	(0.002)	(0.056)	(0.002)	(0.073)	(0.004)
*Van*1	-0.049	0.131***	0.049**	0.137***	0.125***	0.117***	0.092***	0.081***
	(0.066)	(0.007)	(0.021)	(0.003)	(0.026)	(0.004)	(0.034)	(0.007)
*SUV*1	0.045	0.067***	0.050***	0.046***	0.071***	0.030***	0.065***	0.007
	(0.043)	(0.006)	(0.011)	(0.002)	(0.012)	(0.003)	(0.018)	(0.005)
*Gasoline*1		-1.425***		-1.635***		-1.277***		0.100*
		(0.174)		(0.080)		(0.104)		(0.056)
*Diesel*1		-1.494***		-1.772***		-1.431***		-0.130**
		(0.174)		(0.080)		(0.104)		(0.058)
*Ntrlgas*1		-1.724***		-1.737***		-1.405***		na
		(0.245)		(0.087)		(0.110)		na
*Lm*2			-0.161***		-0.149***		-0.176***	
			(0.021)		(0.021)		(0.030)	
*Lm*3					-0.175***		-0.120***	
					(0.021)		(0.030)	
*Lm*4							-0.114***	
							(0.030)	
Constant	8.385***	2.681***	9.967***	2.551***	12.206***	2.496***	12.937***	0.460***
	(1.241)	(0.261)	(0.429)	(0.108)	(0.642)	(0.148)	(1.029)	(0.175)
R^2	0.109	0.522	0.0743	0.5267	0.0205	0.5756	0.0626	0.5209
N	14619	14619	79946	79946	47982	47982	16584	16584

Notes: 1. Standard errors in parentheses. 2. * p<0.10, ** p<0.05, *** p<0.01. 3. na stands for not available.

Table 3.4: OLS regression results[1]

	1-vehicle	2-vehicle	3-vehicle	4-vehicle
	$Lm1$	$Lm1$	$Lm1$	$Lm1$
$Lmpg1$	1.964***	1.756***	1.893***	1.937***
	(0.026)	(0.011)	(0.014)	(0.024)
Lp_F1	-0.794***	-0.414***	-0.323***	0.059
	(0.130)	(0.052)	(0.070)	(0.120)
$Lm2$		0.041***	0.019***	0.008
		(0.003)	(0.004)	(0.006)
$Lm3$			0.015***	0.020***
			(0.004)	(0.006)
$Lm4$				0.010
				(0.006)
R^2	0.337	0.309	0.335	0.348
N	14619	79946	47982	16584

Notes: 1. The same explanatory variables as those in system (3) are controlled for, but only some coefficient estimates are reported in this table. 2. Standard errors in parentheses. 3. * p<0.10, ** p<0.05, *** p<0.01.

Glossary of Terms

Running exhaust tailpipe emissions while a vehicle is driving and idling as part of normal driving, say at intersections.

Idle exhaust tailpipe emissions from heavy-duty vehicles while loading or unloading goods.

Starting exhaust tailpipe emissions from starting a catalyst-equipped vehicle.

Diurnal evaporative HC emissions from a sitting vehicle during daytime when the ambient temperature is rising; excludes hot soak.

Resting loss evaporative HC emissions from a sitting vehicle while the ambient temperature is either constant or decreasing; excludes hot soak.

Hot soak evaporative HC emissions immediately emitted from a vehicle that has just ended its trip.

Running loss evaporative HC emissions from an operating vehicle; caused by fuel losses from the fuel system.

Tire wear particulate matter emissions from tire wear.

Brake wear particulate matter emissions caused by brake use.

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Appendix

Table A1.1: RFG regulation details (In-Out Table)[1]

State	In year	# of In	Out year	# of Out	VOCs control period start date	end date
AZ	1997	1	1998[2]	1	1-Jun	30-Sep
Los San Diego Angeles-San Diego, CA	1995	6	1996[3]	6	1-Jun	15-Sep
CT	1995	8			1-Jun	15-Sep
DE	1995	3			1-Jun	15-Sep
IL	1995	8			1-Jun	15-Sep
IN	1995	2			1-Jun	15-Sep
KY	1995	6			1-Jun	15-Sep
ME	1995	7	1999[4]	7	1-Jun	15-Sep
MD	1995	13			1-Jun	15-Sep
MA	1995	14			1-Jun	15-Sep
St. Louis, MO	1999	5			1-Jun	15-Sep
NH	1995	4			1-Jun	15-Sep
NJ	1995	21			1-Jun	15-Sep
NY	1995	13			1-Jun	15-Sep
PA	1995	5			1-Jun	15-Sep
RI	1995	5			1-Jun	15-Sep
Dallas & Houston, TX	1995	12			1-Jun	15-Sep
VA	1995	28			1-Jun	15-Sep
WI	1995	6			1-Jun	15-Sep
Washington DC	1995	1			1-Jun	15-Sep
State-specific reformulation						
AZ (AZCBG)	1998	1			1-Jun	30-Sep
CA (CARB)	1996	58			varies	varies

Notes: 1. Some independent cities or areas are not a part of any county, but still are treated as counties in this table and our study. 2. Adopted Arizona Cleaner Burning Gasoline program in 1998. 3. Converted into CARB in 1996. 4. Converted from RFG to 7.8 RVP.

Sources: 1. Auffhammer and Kellogg, 2010. 2. The Code of Federal Regulations, 40 CFR, Part 80.70. 3. US EPA, Fuels and Fuel Additives, RFG Areas, available at http://www.epa.gov/otaq/fuels/gasolinefuels/rfg/areas.htm. 4. Reformulated gasoline (RFG) covered areas within 200 miles of a Marathon terminal or Marathon exchange or throughput terminal. RFG Attachment I. Marathon Petroleum Corporation.

Table A1.2: RVP phase II regulation details (In-Out Table)[1]

Area (or State)	In year	# of In	Out year	# of Out	Start date	End date	RVP value
Birmingham, AL[2]	1992	2			1-Jun	15-Sep	7.8
Birmingham, AL	1998	2			1-Jun	15-Sep	7.0
AZ	1992	1	1997[3]	1	1-Jun	15-Sep	7.8
Los Angeles-San Diego, CA	1992	6	1995[3]	6	1-May	31-Oct	7.8
rest of the state, CA	1992	52	1996[4]	52	varies	varies	7.8
CO	1992	6			1-Jun	15-Sep	7.8
FL	1992	6			1-Jun	15-Sep	7.8
Atlanta, GA[2]	1992	13			1-Jun	15-Sep	7.8
Atlanta, GA	1999	13			1-Jun	15-Sep	7.0
GA (excluding Atlanta)	1999	12			1-Jun	15-Sep	7.0
GA (excluding Atlanta)	2003	20			1-Jun	15-Sep	7.0
IL	1995	3			1-Jun	15-Sep	7.2
IN	1996	2			1-Jun	15-Sep	7.8
Kansas City, KS[2]	1992	2			1-Jun	15-Sep	7.8
Kansas City, KS[2]	1997	2			1-Jun	15-Sep	7.2
Kansas City, KS	2001	2			1-Jun	15-Sep	7.0
LA	1992	17			1-Jun	15-Sep	7.8
ME	1999	7			1-May	15-Sep	7.8
MD	1992	12	1995[3]	12	1-Jun	15-Sep	7.8
MI	1996	7			1-Jun	15-Sep	7.8
Kansas City, MO[2]	1992	3			1-Jun	15-Sep	7.8
Kansas City, MO[2]	1997	3			1-Jun	15-Sep	7.2
Kansas City, MO	2001	3			1-Jun	15-Sep	7.0
St. Louis, MO	1992	5	1999[3]	5	1-Jun	15-Sep	7.8
NC	1992	9			1-Jun	15-Sep	7.8
NV	1992	1			1-Jun	15-Sep	7.8
OR	1992	5			1-Jun	15-Sep	7.8
PA	1998	7			1-Jun	15-Sep	7.8
Knoxville, TN	1992	1	1993[5]	1	1-Jun	15-Sep	7.8
Memphis & Nashville, TN	1992	6			1-Jun	15-Sep	7.8
Beaumont, TX	1992	3			1-Jun	15-Sep	7.8

Dallas & Houston, TX	1992	12	1995[3]	12	1-Jun	15-Sep	7.8
EI Paso, TX[2]	1992	1			1-Jun	15-Sep	7.8
EI Paso, TX	1996	1			1-Jun	15-Sep	7.0
Victoria, TX[2]	1992	1			1-Jun	15-Sep	7.8
Eastern TX (w/o Dallas&Houston)	2000	94			1-May	15-Oct	7.8
VA	1992	28	1995[3]	28	1-Jun	15-Sep	7.8
Washington DC	1992	1	1995[3]	1	1-Jun	15-Sep	7.8
All other states	1992				1-Jun	15-Sep	9.0

Notes:1. Some independent cities or areas are not a part of any county, but still are treated as counties in this table and our study. 2. A more stringent RVP requirement was applied in the following summer. 3. Converted into RFG. 4. Converted into CARB. 5. The regulated areas no longer implemented the RVP program in the following period due to redesignation to attainment.

Sources: 1. Auffhammer and Kellogg, 2010. 2. The Code of Federal Regulations, 40 CFR, Part 80.70. 3. US EPA, Guide on Federal and State RVP Standards for Conventional Gasoline Only, EPA-420-B- 10-018, March, 2010. 4. US EPA, Guide on Federal and State RVP Standards for Conventional Gasoline Only, EPA420-B- 05-012, November, 2005. 5. US EPA, Guide on Federal and State RVP Standards for Conventional Gasoline Only, EPA420-B- 01-003, March, 2001. 6. Reformulated gasoline (RFG) covered areas within 200 miles of a Marathon terminal or Marathon exchange or throughput terminal. RFG Attachment I. Marathon Petroleum Corporation. 7. Map retrieved from United Way of Metropolitan Atlanta-County Offices.

Table A1.3: OXY regulation details (In-Out Table)[1]

State	MSA/CMSA	In year	# of In	Out year	# of Out	Start date	End date	Oxygen content
AK	Anchorage[2]	1995	1	2004	1	1-Nov	28-Feb	2.70%
AK	Fairbanks[3]	0						
AZ	Phoenix[2]	1989	1			2-Nov	31-Mar	3.50%
AZ	Tucson	1989	1			1-Oct	31-Mar	1.80%
CA[4]		1992	19	1998	19	varies	varies	2.70%
CO	Colorado Springs[2]	1992	1	2000	1	1-Nov	7-Feb	3.10%
CO	Denver-Boulder[2]	1992	7	2007	7	1-Nov	31-Jan	1.50%
CO	Fort Collins-Loveland[2]	1992	1	2004	1	1-Nov	7-Feb	3.10%
CT	Hartford	1992	3	1996	3	1-Nov	28-Feb	2.70%
CT	NY-Northern NJ-Long Island-CT[2]	1992	3	2000	3	1-Oct	28-Feb	2.70%
DC	Washington	1992	1	1996	1	1-Nov	28-Feb	2.70%
MA	Boston-Lawrence-Salem	1992	6	1996	6	1-Nov	28-Feb	2.70%
MD	Baltimore	1992	6	1995	6	1-Nov	28-Feb	2.70%
MD	Philadelphia-Wilmington, Trenton	1992	1	1996	1	1-Nov	28-Feb	2.70%
MD	Washington	1992	5	1996	5	1-Nov	28-Feb	2.70%
MN	Duluth	1992	1	1994	1	1-Oct	31-Jan	2.70%
MN	Minneapolis-St. Paul[2, 5]	1992	10			year-round		3.10%
MT	Missoula	1992	1			1-Nov	28-Feb	2.70%
NC	Greensboro-Winston-Salem-High Point	1992	7	1994	7	1-Nov	28-Feb	2.70%
NC	Raleigh-Durham	1992	4	1995	4	1-Nov	28-Feb	2.70%
NJ	NY-Northern NJ-Long Island-CT[2]	1992	13	1999	13	1-Oct	28-Feb	2.70%
NJ	Philadelphia-Wilmington, Trenton	1992	8	1996	8	1-Nov	28-Feb	2.70%
NM	Albuquerque	1989	1			1-Nov	28-Feb	2.70%
NV	Las Vegas[2]	1989	1			1-Oct	31-Mar	3.50%
NV	Reno	1989	1			1-Oct	31-Jan	2.70%
NY	NY-Northern NJ-Long Island-CT[2]	1992	11	2000	11	1-Oct	28-Feb	2.70%
NY	Syracuse	1992	3	1994	3	1-Nov	28-Feb	2.70%
OH	Cleveland-Akron-Lorain	1992	7	1994	7	1-Nov	28-Feb	2.70%
OR	Grant's Pass	1992	1	2000	1	1-Nov	28-Feb	2.70%
OR	Klamath	1992	1	2001	1	1-Nov	28-Feb	2.70%

OR	Medford	1992	1	2002	1	1-Nov	28-Feb	2.70%
OR	Portland	1992	4	2008	4	1-Nov	28-Feb	2.70%
PA	Philadelphia-Wilmington, Trenton	1992	5	1996	5	1-Nov	28-Feb	2.70%
TN	Memphis	1992	2	1994	2	1-Nov	28-Feb	2.70%
TX	El Paso[2]	1992	1			1-Oct	31-Mar	2.70%
UT	Ogden[3]	0						
UT	Provo-Orem[2]	1992	1	2006	1	1-Nov	28-Feb	2.70%
UT	Salt Lake City[3]	0						
VA	Washington	1992	10	1996	10	1-Nov	28-Feb	2.70%
WA	Seattle-Tacoma	1992	3	1996	3	1-Nov	28-Feb	2.70%
WA	Spokane	1992	1	2005	1	1-Sep	28-Feb	3.50%
WA	Vancouver	1992	1	1996	1	1-Nov	28-Feb	2.70%

Notes: 1. Some independent cities or areas are not a part of any county, but still are treated as counties in this table and our study. 2. The OXY control period and/or oxygen content requirements had been revised, and only the most recent requirements were listed in the table. 3. This area was not implementing an OXY program even though the area had been designated as a nonattainment area. 4. All areas in CA were required to use CA Phase II fuel (a 1.8%-2.2% of oxygen content) starting from June 1, 1996. 5. Only these 10 counties in Minnesota were incorporated into the OXY-treated group in our study according to Documentation for the onroad national emissions inventory (NEI) for base years 1970-2002, though Minnesota adopted a statewide oxygen mandate throughout the year beginning on October 1, 1997.

Sources: 1. US EIA, Areas Participating in the Oxygenated Gasoline Program, available at http://www.eia.gov/emeu/steo/pub/special/oxy2.html. 2. US EPA, State Winter Oxygenated Fuel Program Requirements for Attainment or Maintenance of CO NAAQS, EPA420-B-08-006, January, 2008. 3. US EPA, State Winter Oxygenated Fuel Program Requirements for Attainment or Maintenance of CO NAAQS, EPA420-B-05-013, November, 2005. 4. US EPA, State Winter Oxygenated Fuel Programs, October, 2001, at http://www.epa.gov/oms/regs/fuels/oxy-area.pdf. 5. US EPA, State Winter Oxygenated Fuel Programs, December 6, 1999, at http://www.p2pays.org/ref/07/06823.pdf. 6. US EPA, State Winter Oxygenated Fuel Programs, June 16, 1999. 7. US EIA, Oxygenated Gasoline Control Area Pollutions Excel spreadsheet, available at ftp://ftp.eia.doe.gov/pub/forecasting/steo/special/rpt/oxy2.xls. 8. Documentation for the onroad national emissions inventory (NEI) for base years 1970-2002.

Table A1.4: The scope of the purified RFG-treated counties (1996 switch in)

State	County	State	County	State	County	State	County
CT	Hartford Co	MD	Baltimore Co	NJ	Camden Co	VA	Fairfax Co
CT	Middlesex Co	MD	Calvert Co	NJ	Cape May Co	VA	Hanover Co
CT	New London Co	MD	Carroll Co	NJ	Cumberland Co	VA	Henrico Co
CT	Tolland Co	MD	Cecil Co	NJ	Gloucester Co	VA	James City Co
CT	Windham Co	MD	Charles Co	NJ	Mercer Co	VA	Loudoun Co
DE	Kent Co	MD	Frederick Co	NJ	Salem Co	VA	Prince William Co
DE	New Castle Co	MD	Harford Co	NY	Dutchess Co	VA	Stafford Co
DE	Sussex Co	MD	Howard Co	NY	Essex Co	VA	York Co
DC	Washington city	MD	Kent Co	PA	Bucks Co	VA	Alexandria city
IL	Cook Co	MD	Montgomery Co	PA	Chester Co	VA	Chesapeake city
IL	DuPage Co	MD	Prince George's Co	PA	Delaware Co	VA	Colonial Heights city
IL	Grundy Co	MD	Queen Anne's Co	PA	Montgomery Co	VA	Fairfax city
IL	Kane Co	MD	Baltimore city	PA	Philadelphia Co	VA	Falls Church city
IL	Kendall Co	MA	Barnstable Co	RI	Bristol Co	VA	Hampton city
IL	Lake Co	MA	Berkshire Co	RI	Kent Co	VA	Hopewell city
IL	McHenry Co	MA	Bristol Co	RI	Newport Co	VA	Manassas city
IL	Will Co	MA	Dukes Co	RI	Providence Co	VA	Manassas Park city
IN	Lake Co	MA	Essex Co	RI	Washington Co	VA	Newport News city
IN	Porter Co	MA	Franklin Co	TX	Brazoria Co	VA	Norfolk city
KY	Boone Co	MA	Hampden Co	TX	Chambers Co	VA	Poquoson city
KY	Bullitt Co	MA	Hampshire Co	TX	Collin Co	VA	Portsmouth city
KY	Campbell Co	MA	Middlesex Co	TX	Dallas Co	VA	Richmond city
KY	Jefferson Co	MA	Nantucket Co	TX	Denton Co	VA	Suffolk city
KY	Kenton Co	MA	Norfolk Co	TX	Fort Bend Co	VA	Virginia Beach city
KY	Oldham Co	MA	Plymouth Co	TX	Galveston Co	VA	Williamsburg city
ME	Androscoggin Co	MA	Suffolk Co	TX	Harris Co	WI	Kenosha Co
ME	Cumberland Co	MA	Worcester Co	TX	Liberty Co	WI	Milwaukee Co
ME	Kennebec Co	NH	Hillsborough Co	TX	Montgomery Co	WI	Ozaukee Co
ME	Knox Co	NH	Merrimack Co	TX	Tarrant Co	WI	Racine Co
ME	Lincoln Co	NH	Rockingham Co	TX	Waller Co	WI	Washington Co
ME	Sagadahoc Co	NH	Strafford Co	VA	Arlington Co	WI	Waukesha Co

ME	York Co	NJ	Atlantic Co	VA	Charles City Co
MD	Anne Arundel Co	NJ	Burlington Co	VA	Chesterfield Co
Total	130				

Table A1.5: The scope of the RVP-treated counties (1996 switch in)

State	County	State	County	State	County	State	County
AL	Jefferson Co	IL	Madison Co	LA	St. James Par	NC	Forsyth Co
AL	Shelby Co	IL	Monroe Co	LA	St. Mary Par	NC	Gaston Co
FL	Broward Co	IL	St. Clair Co	LA	West Baton Rouge Par	NC	Granville Co
FL	Duval Co	IN	Clark Co	MI	Livingston Co	NC	Guilford Co
FL	Hillsborough Co	IN	Floyd Co	MI	Macomb Co	NC	Mecklenburg Co
FL	Miami-Dade Co	KS	Johnson Co	MI	Monroe Co	NC	Wake Co
FL	Palm Beach Co	KS	Wyandotte Co	MI	Oakland Co	OR	Marion Co
FL	Pinellas Co	LA	Ascension Par	MI	St. Clair Co	OR	Polk Co
GA	Butts Co	LA	Beauregard Par	MI	Washtenaw Co	TN	Davidson Co
GA	Cherokee Co	LA	Calcasieu Par	MI	Wayne Co	TN	Rutherford Co
GA	Clayton Co	LA	East Baton Rouge Par	MO	Clay Co	TN	Shelby Co
GA	Cobb Co	LA	Grant Par	MO	Franklin Co	TN	Sumner Co
GA	Coweta Co	LA	Iberville Par	MO	Jackson Co	TN	Williamson Co
GA	DeKalb Co	LA	Jefferson Davis Par	MO	Jefferson Co	TN	Wilson Co
GA	Douglas Co	LA	Lafayette Par	MO	Platte Co	TX	Hardin Co
GA	Fayette Co	LA	Lafourche Par	MO	St. Charles Co	TX	Jefferson Co
GA	Fulton Co	LA	Livingston Par	MO	St. Louis Co	TX	Orange Co
GA	Gwinnett Co	LA	Orleans Par	MO	St. Louis city	TX	Victoria Co
GA	Henry Co	LA	Pointe Coupee Par	NC	Davidson Co	UT	Davis Co
GA	Paulding Co	LA	St. Bernard Par	NC	Davie Co	UT	Salt Lake Co
GA	Rockdale Co	LA	St. Charles Par	NC	Durham Co		
Total	83						

Table A1.6: The scope of the RVP-treated counties (1996 later switch in)

State	County	State	County	State	County	State	County
1998-switch-in (7 counties)							
PA	Allegheny Co	PA	Beaver Co	PA	Fayette Co	PA	Westmoreland Co
PA	Armstrong Co	PA	Butler Co	PA	Washington Co		
1999-switch-in (12 counties)							
GA	Barrow Co	GA	Dawson Co	GA	Haralson Co	GA	Pickens Co
GA	Bartow Co	GA	Forsyth Co	GA	Jackson Co	GA	Spalding Co
GA	Carroll Co	GA	Hall Co	GA	Newton Co	GA	Walton Co
2000-switch-in (94 counties)							
TX	Anderson Co	TX	Ellis Co	TX	Kaufman Co	TX	Rockwall Co
TX	Angelina Co	TX	Falls Co	TX	Lamar Co	TX	Rusk Co
TX	Aransas Co	TX	Fannin Co	TX	Lavaca Co	TX	Sabine Co
TX	Atascosa Co	TX	Fayette Co	TX	Lee Co	TX	San Augustine Co
TX	Austin Co	TX	Franklin Co	TX	Leon Co	TX	San Jacinto Co
TX	Bastrop Co	TX	Freestone Co	TX	Limestone Co	TX	San Patricio Co
TX	Bee Co	TX	Goliad Co	TX	Live Oak Co	TX	Shelby Co
TX	Bell Co	TX	Gonzales Co	TX	McLennan Co	TX	Smith Co
TX	Bexar Co	TX	Grayson Co	TX	Madison Co	TX	Somervell Co
TX	Bosque Co	TX	Gregg Co	TX	Marion Co	TX	Titus Co
TX	Bowie Co	TX	Grimes Co	TX	Matagorda Co	TX	Travis Co
TX	Brazos Co	TX	Guadalupe Co	TX	Milam Co	TX	Trinity Co
TX	Burleson Co	TX	Harrison Co	TX	Morris Co	TX	Tyler Co
TX	Caldwell Co	TX	Hays Co	TX	Nacogdoches Co	TX	Upshur Co
TX	Calhoun Co	TX	Henderson Co	TX	Navarro Co	TX	Van Zandt Co
TX	Camp Co	TX	Hill Co	TX	Newton Co	TX	Walker Co
TX	Cass Co	TX	Hood Co	TX	Nueces Co	TX	Washington Co
TX	Cherokee Co	TX	Hopkins Co	TX	Panola Co	TX	Wharton Co
TX	Colorado Co	TX	Houston Co	TX	Parker Co	TX	Williamson Co
TX	Comal Co	TX	Hunt Co	TX	Polk Co	TX	Wilson Co
TX	Cooke Co	TX	Jackson Co	TX	Rains Co	TX	Wise Co
TX	Coryell Co	TX	Jasper Co	TX	Red River Co	TX	Wood Co
TX	Delta Co	TX	Johnson Co	TX	Refugio Co		
TX	DeWitt Co	TX	Karnes Co	TX	Robertson Co		

Table A1.7: The scope of the OXY-treated counties (switch in and out)

State	County	State	County	State	County	State	County
1996-switch-in (21 counties)							
AK	Anchorage Municipality	MN	Chisago Co	MN	Washington Co	OR	Yamhill Co
CO	El Paso Co	MN	Dakota Co	MN	Wright Co	UT	Utah Co
CO	Larimer Co	MN	Hennepin Co	MT	Missoula Co	WA	Spokane Co
CO	Weld Co	MN	Isanti Co	OR	Jackson Co		
MN	Anoka Co	MN	Ramsey Co	OR	Josephine Co		
MN	Carver Co	MN	Scott Co	OR	Klamath Co		
2000-switch-out (2 counties)							
CO	El Paso Co	OR	Josephine Co				
2001-switch-out (1 counties)							
OR	Klamath Co						
2002-switch-out (1 counties)							
OR	Jackson Co						

Table A1.8: The scope of regulation overlap including RFG

RFG&CARB overlap		RFG&OXY overlap					
State	County	State	County	State	County	State	County
CA	Los Angeles	CT	Fairfield	NJ	Morris	NY	Nassau
CA	Orange	CT	Litchfield	NJ	Ocean	NY	New York
CA	Riverside	CT	New Haven	NJ	Passaic	NY	Orange
CA	San Bernardino	NJ	Bergen	NJ	Somerset	NY	Putnam
CA	San Diego	NJ	Essex	NJ	Sussex	NY	Queens
CA	Ventura	NJ	Hudson	NJ	Union	NY	Richmond
		NJ	Hunterdon	NJ	Warren	NY	Rockland
		NJ	Middlesex	NY	Bronx	NY	Suffolk
		NJ	Monmouth	NY	Kings	NY	Westchester

Table A1.9: RVP effects, on-road vehicles

RVP	1996-switch-in	1998, 1999, and 2000-switch-in				
	1990-1996	1-year-in	2-year-in	3-year-in	4-year-in	5-year-in
VOCs emissions per capita (kgs)						
		Generalized effects				
Trvpdafter	2.940**	-0.323	-0.703	-2.864***	-2.021	-2.239
	(1.476)	(1.012)	(0.982)	(1.001)	(1.533)	(3.250)
		Separate effects				
TrvpdafterP1		-0.103	-0.632	0.641	0.420	-2.239
		(2.011)	(2.167)	(1.784)	(1.784)	(3.250)
TrvpdafterP2		-0.533	-0.0299	0.311	-4.124**	
		(1.645)	(1.459)	(1.469)	(1.911)	
TrvpdafterP3		-0.108	-0.388	-5.161***		
		(1.368)	(1.246)	(1.156)		
VOCs emissions per square mile (tons)						
		Generalized effects				
Trvpdafter	-6.657***	-0.0875	-0.216**	-0.542***	-1.391**	-1.881
	(1.131)	(0.0886)	(0.0984)	(0.130)	(0.561)	(1.425)
		Separate effects				
TrvpdafterP1		-0.373	-0.915	-1.461	-1.829	-1.881
		(1.032)	(1.084)	(1.237)	(1.275)	(1.425)
TrvpdafterP2		-0.140	-0.269	-0.401	-1.128***	
		(0.316)	(0.301)	(0.309)	(0.408)	
TrvpdafterP3		-0.0788	-0.168**	-0.548***		
		(0.0743)	(0.0798)	(0.116)		

Notes: 1. The numbers in parentheses are the standard errors. 2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A1.10: OXY effects, on-road vehicles

OXY	1996-switch-in	2000, 2001, and 2002-switch-out		
	1990-1996	1-year-out	2-year-out	3-year-out
CO emissions per capita (kgs)				
		Generalized effects		
Toxydafter	-13.78	13.02	107.4	22.57
	(52.73)	(58.64)	(73.25)	(91.18)
		Separate effects		
ToxydafterP1		30.86	15.95	22.57
		(26.90)	(35.03)	(91.18)
ToxydafterP2		-9.401	295.1***	
		(7.664)	(11.59)	
ToxydafterP3		3.788		
		(10.53)		
CO emissions per square mile (tons)				
		Generalized effects		
Toxydafter	-67.39**	2.186	2.419	4.134
	(26.87)	(4.922)	(6.801)	(9.274)
		Separate effects		
ToxydafterP1		3.045	1.633	4.134
		(10.25)	(9.903)	(9.274)
ToxydafterP2		0.656**	4.073***	
		(0.255)	(0.312)	
ToxydafterP3		1.760***		
		(0.295)		

Notes: 1. The numbers in parentheses are the standard errors. 2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A1.11: RVP effects, off-road engines and vehicles

RVP	1996-switch-in	1998, 1999, and 2000-switch-in				
	1990-1996	1-year-in	2-year-in	3-year-in	4-year-in	5-year-in
VOCs emissions per capita (kgs)						
		Generalized effects				
Trvpdafter	-0.170	11.06**	10.59**	-2.252	-7.651	0.0220
	(7.081)	(5.188)	(5.305)	(5.193)	(10.10)	(23.57)
		Separate effects				
TrvpdafterP1		-7.902	17.45	-13.38	-11.85	0.0220
		(22.96)	(24.49)	(23.43)	(23.54)	(23.57)
TrvpdafterP2		-11.20	6.577	-16.34**	-8.404	
		(7.021)	(6.095)	(7.192)	(6.567)	
TrvpdafterP3		18.59**	17.78**	-7.188		
		(9.061)	(7.777)	(6.336)		
VOCs emissions per square mile (tons)						
		Generalized effects				
Trvpdafter	-0.0806	0.0470	0.0270	0.108	0.0957	-0.232
	(0.432)	(0.136)	(0.135)	(0.165)	(0.289)	(0.419)
		Separate effects				
TrvpdafterP1		-0.168	-0.00854	-0.254	-0.238	-0.232
		(0.295)	(0.298)	(0.300)	(0.299)	(0.419)
TrvpdafterP2		-0.162	-0.113	-0.306	0.235	
		(0.334)	(0.326)	(0.325)	(0.415)	
TrvpdafterP3		0.128	0.0864	0.00806		
		(0.156)	(0.154)	(0.189)		

Notes: 1. The numbers in parentheses are the standard errors. 2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A1.12: OXY effects, off-road engines and vehicles

OXY	1996-switch-in	2000, 2001, and 2002-switch-out		
	1990-1996	1-year-out	2-year-out	3-year-out
CO emissions per capita (kgs)				
		Generalized effects		
Toxydafter	-11.36	-0.123	16.21	5.236
	(30.56)	(17.70)	(29.24)	(34.75)
		Separate effects		
ToxydafterP1		-1.057	4.253	5.236
		(18.95)	(21.40)	(34.75)
ToxydafterP2		2.966	43.25	
		(13.71)	(36.75)	
ToxydafterP3		11.45		
		(30.51)		
CO emissions per square mile (tons)				
		Generalized effects		
Toxydafter	0.315	-0.0295	0.260	4.13e-04
	(6.702)	(1.075)	(1.110)	(0.310)
		Separate effects		
ToxydafterP1		-0.0779	0.0477	4.13e-04
		(3.041)	(2.973)	(0.310)
ToxydafterP2		0.0806	0.814***	
		(0.165)	(0.195)	
ToxydafterP3		0.203		
		(0.209)		

Notes: 1. The numbers in parentheses are the standard errors. 2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A1.13: The effect of regulation overlap on pollution reduction (n=5348)

Pollutant		Levels	Per capita	Density
VOCs	Trfgdafter	-14580.6***	5.186***	-50.25***
		(2729.6)	(1.687)	(10.76)
	r2	0.933	0.335	0.943
NOx	Trfgdafter	-7449.3***	1.124	-24.16***
		(1633.8)	(3.88)	(5.861)
	r2	0.969	0.11	0.981
CO	Trfgdafter	-152920.8***	63.31***	-501.9***
		(29211.5)	(23.19)	(110.6)
	r2	0.928	0.26	0.948

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.010

Table A2.1: Expected VMT schedules by vehicle type (miles)

Age	Auto	Vans	SUVs	Trucks	Category 3	Auto	Vans	SUVs	Trucks	Category 3
	Trade-in vehicles					Replacement vehicles[1]				
1						13500	14084	13719	13878	14725
2						13149	13635	13274	13437	13114
3						12748	13118	12763	12930	12461
4						12294	12537	12189	12358	12311
5						11787	11899	11560	11730	11765
6						11229	11211	10884	11053	10808
7						10628	10487	10173	10340	10178
8						9991	9741	9440	9605	9476
9						9330	8986	8700	8861	8711
10						8656	8236	7967	8122	7986
11						7676	7504	7252	7401	6899
12						6380	6798	6563	6705	6276
13						5163	6055	5840	5973	5665
14						4086	5363	5167	5291	4963
15						3179	4727	4550	4664	4316
16	6318	9242	8783	8438	7987	2440	4150	3990	4095	3612
17	4787	8090	7680	7375	6982	1856	3632	3489	3584	3157
18	3600	7064	6699	6430	6082	1401	3171	3043	3130	2750
19	2697	6160	5837	5601	5385	1053	2765	2651	2730	2435
20	2018	5366	5080	4874	4871	790	2408	2307	2378	2203
21	1507	4677	4424	4244	3880	592	2098	2009	2073	1754
22	1127	4076	3853	3696	3560	443	1829	1750	1807	1610
23	846	3557	3362	3226	3155	333	1596	1526	1577	1427
24	636	3112	2941	2822	2668	250	1396	1335	1380	1206
25	479	2723	2574	2470	2335	189	1222	1168	1208	1056

Note: 1. Only the VMTs for the retired vehicles of age 16 and the replacement vehicles of age 1 and also with the residual lifetime of 6.60 years are listed due to space limit. For more details, see footnote 18 in the main body of the paper. 2. The VMTs of vehicles of age 24 are used to represent the VMTs after a vehicle's age exceeds 24, which are multiplied by the vehicle survival rates to obtained the expected VMTs for the vehicles of age older than 24. The table does not list the VMTs for the vehicles of age older than 25 due to space limit.

Table A2.2: Vehicle counts and fuel economy by category of the trade-in vehicles

Age	Auto		Van		SUV		Truck		Category 3[1]
	mpg	count	mpg	count	mpg	count	mpg	count	count
Trade-in vehicles									
3					16.00	2			
4			14.00	1			12.00	1	
5	17.00	2	16.50	8	15.75	4	15.75	4	
6	17.43	7	16.13	23	16.16	25	15.59	17	
7	17.33	15	16.59	85	15.88	104	16.04	72	
8	17.74	39	17.18	285	15.90	589	15.86	159	
9	17.88	116	17.49	577	16.07	1055	15.45	431	22
10	17.71	224	16.83	852	15.56	2000	15.68	579	23
11	17.93	280	17.13	1268	15.08	2783	15.35	769	24
12	17.99	458	17.25	1595	15.28	3172	15.19	1014	23
13	17.97	629	17.18	2063	15.12	2961	15.35	1024	25
14	17.95	674	17.32	1970	15.23	2967	15.11	842	20
15	17.78	1204	17.14	2435	15.00	3032	14.56	935	22
16	17.78	1304	16.77	1853	15.13	2535	15.06	1120	19
17	17.65	1022	17.06	1784	15.37	1997	15.37	861	14
18	17.53	1303	16.45	1167	15.08	1371	15.02	837	22
19	17.54	1485	17.10	1193	15.48	1192	15.27	762	28
20	17.47	1522	16.20	741	15.18	750	14.74	889	42
21	17.35	1234	15.89	672	15.31	750	14.91	813	49
22	17.22	962	15.76	369	15.29	486	15.04	624	24
23	17.13	803	14.82	284	15.26	375	15.40	447	17
24	17.05	671	15.06	263	15.13	233	15.24	474	24
25	16.80	643	14.11	194	14.13	138	14.29	324	17
26	16.04	137	13.47	51	13.90	42	14.14	65	6
sum		14734		19733		28563		13063	421
Replacement vehicles									
2007	27.51	49	19.5	2	22.44	25	18.29	21	1
2008	26.08	550	17.88	34	21.43	292	18.33	147	31
2009	27.51	30982	20.34	1047	22.39	14583	18.71	6193	95
2010	32.52	17983	19.02	686	21.98	3057	18.45	735	1
sum		49564		1769		17957		7096	128

Table A2.3: Vehicle survival rates by vehicle category

Passenger cars													
Vehage	1	2	3	4	5	6	7	8	9	10	11	12	13
Survival rate	0.99	0.9831	0.9731	0.9593	0.9413	0.9188	0.8918	0.8604	0.8252	0.7866	0.717	0.6125	0.5094
Vehage	14	15	16	17	18	19	20	21	22	23	24	25	
Survival rate	0.4142	0.3308	0.2604	0.2028	0.1565	0.12	0.0916	0.0696	0.0527	0.0399	0.0301	0.0227	
Light duty vehicles													
Vehage	1	2	3	4	5	6	7	8	9	10	11	12	13
Survival rate	0.9741	0.9603	0.942	0.919	0.8913	0.859	0.8226	0.7827	0.7401	0.6956	0.6501	0.604	0.5517
Vehage	14	15	16	17	18	19	20	21	22	23	24	25	26
Survival rate	0.5009	0.4522	0.4062	0.3633	0.3236	0.2873	0.2542	0.2244	0.1975	0.1735	0.1522	0.1332	0.1165
Vehage	27	28	29	30	31	32	33	34	35	36			
Survival rate	0.1017	0.0887	0.0773	0.0673	0.0586	0.0509	0.0443	0.0385	0.0334	0.029			

Source: Table 3 (p. 8) and Table 4 (p. 11) from “Vehicle Survivability and Travel mileage Schedules” by Lu (2006).

Table A2.4: Emission factors of ROG and CO2 for passenger cars by vehicle age

	ROG						CO2	
vehage	runex	runls	strex	diurn	htsk	restl	runex	strex
	(g/mile)		(g/vehicle/day)				(g/mile)	(g/vehicle/day)
1	0.006172	0.009938	0.21888	0.027846	0.03346	0.018126	353.4484	487.3792
2	0.006574	0.011831	0.234812	0.029928	0.041859	0.020406	352.0161	485.2883
3	0.007547	0.01358	0.280449	0.03307	0.054557	0.023869	350.7618	483.9279
4	0.008984	0.015535	0.340536	0.037663	0.073792	0.02918	350.2867	482.8276
5	0.009837	0.01817	0.369735	0.050136	0.117681	0.044117	349.9601	482.0852
6	0.011839	0.024508	0.451574	0.113096	0.307886	0.122298	349.971	480.7917
7	0.023385	0.030565	1.469918	0.146996	0.447842	0.164061	340.9912	445.2737
8	0.026031	0.040441	1.656371	0.197249	0.658686	0.218257	337.8479	437.9961
9	0.027173	0.048408	1.732319	0.23359	0.825712	0.260387	338.8364	437.7595
10	0.028669	0.05575	1.823458	0.269884	0.984568	0.304658	339.4015	435.7723
11	0.037195	0.063316	2.940797	0.306835	1.141259	0.349136	332.179	425.6568
12	0.046101	0.070897	4.160869	0.34235	1.292978	0.392108	334.3867	427.4771
13	0.057574	0.154798	5.486503	1.132505	1.747967	0.627493	336.754	429.8762
14	0.06399	0.191233	6.143503	1.506906	2.055845	0.756683	337.3666	427.8565
15	0.089156	0.226592	7.291793	1.906238	2.455783	0.897737	337.9855	425.5268
16	0.137747	0.245293	7.844678	2.172216	2.798758	1.025348	338.3335	421.7992
17	0.265468	0.249887	9.288199	2.270996	3.145844	1.112354	339.0146	416.9403
18	0.342701	0.255762	10.2656	2.362492	3.486861	1.208038	363.6464	439.9867
19	0.343173	0.259845	10.19396	2.44625	3.868	1.301999	363.496	436.3548
20	0.345732	0.264138	10.14037	2.500396	4.134098	1.413225	363.7483	433.4011
21	0.32987	0.268409	9.850508	2.608492	4.477758	1.537698	363.2498	431.3809
22	0.318081	0.597358	9.355418	2.877179	5.792009	1.824051	363.0769	429.8742
23	0.322987	0.665712	9.037342	3.073181	5.993317	2.005511	362.9634	426.8292
24	0.322206	0.731143	8.638781	3.088202	5.919238	2.139381	363.1246	424.7315
25	0.370022	0.724424	8.661552	3.373529	6.103013	2.344582	384.8473	444.4711

Note: the missing values of the emissions factors are replaced by the values calculated by linear interpolation.

Table A2.5: Regression output for IV regression first stage

Dependent variable	Vehicle fuel efficiency (mpg)	
Gasprice_at purchase	0.170***	(0.020)
CAFE_at puchase	-0.239***	(0.021)
Fuel cost (dollars per gallon)	0.047	(0.068)
HH income (units of 10,000 dollars)	-0.025***	(0.002)
HH size	0.001	(0.011)
Count of vehicle's primary drivers	0.116***	(0.012)
Count of HH workers	0.329***	(0.012)
Adults with children	0.596***	(0.029)
Adults with no children	0.525***	(0.023)
Race is White	-0.136**	(0.064)
Race is African American or Black	-0.351***	(0.073)
Race is Asian only	-0.250***	(0.085)
Race is American Indian or Alaskan Native	0.060	(0.115)
Race is Native Hawaiian or other Pacific	-0.197	(0.170)
Race is Hispanic	-0.087	(0.084)
Race is Multiracial	0.163	(0.123)
Residential density	-0.005	(0.004)
Home is owned	-0.383***	(0.032)
Home locates in a MSA with rail	-0.024	(0.025)
Home locates in an urbanized area	-0.226***	(0.018)
Vehicle age	-0.520***	(0.014)
Vehicle age square	0.030***	(0.001)
Vehicle age cubic	-0.001***	(0.000)
Auto	7.809***	(0.132)
Vans	2.144***	(0.035)
SUVs	0.652***	(0.028)
Acura	1.353***	(0.098)
BMW	-1.877***	(0.093)
Buick	-0.568***	(0.072)
Cadil	-3.077***	(0.085)
Chevr	0.925***	(0.063)
Chrys	-0.256***	(0.076)
Dodge	0.413***	(0.068)

Ford	0.444***	(0.063)
GMC	0.031	(0.076)
Honda	4.696***	(0.065)
Hyund	2.663***	(0.085)
Infin	-1.833***	(0.122)
Isuzu	1.383***	(0.152)
Jeep	0.417***	(0.080)
Kia	1.329***	(0.100)
Lexus	-0.108	(0.084)
Linco	-2.916***	(0.093)
Mazda	2.053***	(0.086)
Merce	-0.582***	(0.092)
Mercu	-1.256***	(0.082)
Mitsu	1.211***	(0.110)
Nissa	1.903***	(0.070)
Oldsm	-0.210**	(0.095)
Plymo	2.314***	(0.131)
Ponti	1.071***	(0.082)
Satur	2.618***	(0.088)
Subar	2.221***	(0.089)
Toyot	3.650***	(0.063)
Volks	2.421***	(0.091)
Volvo	-0.401***	(0.097)
Gasoline	-9.842**	(3.868)
Diesel	-10.927***	(3.868)
Ntrlgas	-13.063***	(3.887)
Constant	32.362***	(3.902)
N	236,933	
r2	0.468	

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.