TRANSPORTATION ECONOMICS AND ENERGY

by

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ABSTRACT

Transportation Economics and Energy

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The overall objective of this research is to study the impacts of technology improvement including fuel efficiency increment, extending the use of natural gas vehicle and electric vehicles on key parameters of transportation. In the first chapter, a simple economic analysis is used in order to demonstrate the adoption rate of natural gas vehicles as an alternative fuel vehicle. The effect of different factors on adoption rate of commuters is calculated in sensitivity analysis.

In second chapter the VMT is modeled and forecasted under influence of CNG vehicles in different scenarios. The VMT modeling is based on the time series data for Washington State. In order to investigate the effect of population growth on VMT, the per capita model is also developed.

In third chapter the effect of fuel efficiency improvement on fuel tax revenue and greenhouse emission is examined. The model is developed based on time series data of Washington State. The rebound effect resulted from fuel efficiency improvement is
estimated and is considered in fuel consumption forecasting. The reduction in fuel tax revenue and greenhouse gas (GHG) emissions as two outcomes of lower fuel consumption are computed. In addition, the proper fuel tax rate to restitute the revenue is suggested.

In the fourth chapter effective factors on electric vehicles (EV) adoption is discussed. The constructed model is aggregated binomial logit share model that estimates the modal split between EV and conventional vehicles for different states over time. Various factors are incorporated in the utility function as explanatory variables in order to quantify their effect on EV adoption choices. The explanatory variables include income, VMT, electricity price, gasoline price, urban area and number of EV stations.
Transportation is one of the major energy consuming sectors in the United States. The continued growth in fuel consumption not only increases dependency on foreign oil but also causes environmental issues due to the emissions of greenhouse gas (GHG). High gasoline consumption in the US transportation sector not only raises concerns regarding national energy security, but also poses many questions regarding the resulting environmental impacts of greenhouse gases emissions. Improvement in automobile fuel economy, increase the use of natural gas vehicles and electric vehicles have been proven to be as the policies in controlling oil demand and GHG emissions in transportation sector around the world.

The core of this research is to conduct the feasibility and efficiency of policies and their effects on key transportation parameters. The major question on which this research focuses is: “How do fuel efficiency improvement, natural gas vehicles and electric vehicles affect key transportation parameters?” Modeling is accomplished in support of the Washington State Department of Transportation. Addressing this question effectively requires the ability to investigate the following issues:

- What will be the adoption rates of natural gas vehicles?
- What is the impact of natural gas vehicles on VMT?
• What is the impact of higher fuel efficiency on vehicle emissions and fuel tax revenue?

• What are the effective factors on electric vehicles adoption?
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CHAPTER 1
INTRODUCTION

In order to meet the demand for petroleum products, the United States is heavily dependent on foreign oil. Compared to other sectors, the US transportation sector has always been the major consumer of petroleum. US Energy Information Administration (EIA, 2011) reported that transportation sector consumed 72% of all petroleum used in the United States. Within the transportation sector, 94% of the energy demand was met by petroleum, 4% was supplied by natural gas, while the remaining 2% was supplied by renewable energy (Mazraati and Shelbi 2011).

The continued growth in the gasoline use increases the dependence on foreign countries, which causes national and economic security issues. High gasoline consumption in the US transportation sector not only raises concerns regarding national energy security, but also poses many questions regarding the resulting environmental impacts of greenhouse gases emissions. For instance, in 2008, the transportation sector emitted 1930 million metric tons of carbon dioxide, which represents a 33.2% share of total carbon dioxide emissions from all sectors (Davis et al. 2010).

In more details, passenger transportation accounts for almost 18% of the energy consumption and 22% of the total greenhouse gas (GHG) emissions in the United States. In addition, approximately 63% of the transportation sector’s total energy consumption and 73% of the transportation sector’s total GHG emissions are share of passenger transportation (Rentziou et al. 2012).
The solutions of these problems depend largely on the policies that can reduce U.S. gasoline consumption by driving less, purchasing more fuel-efficient vehicles, and using alternative fuel vehicles. Each of these policies has different impacts on key transportation parameters.

In this study the goal is to examine and analyze the different aspects of three different policies in order to decrease the gasoline usage:

- Use of natural gas vehicles
- Vehicle’s fuel efficiency improvement
- Use of electric vehicles

Natural gas has the potential to become an attractive substitute for petroleum. Natural gas prices in the U.S. have dropped more than sixty percent from their peak in 2008 and proven reserves are approaching all time high levels (Paltsev et al. 2011; Moniz 2011; Staub 2013). The increasing price for petroleum and decreasing price for natural gas provide a growing cost advantage over gasoline.

There is an ongoing debate on how the adoption of natural gas vehicles will affect future travel demand. Vehicle Miles Traveled (VMT) is one of the most common measures estimating travel demand in the U.S. and has historically been used to determine the need for new infrastructure. As the availability of traditional energy resources and funding for new infrastructure decrease, the need of forecasting future VMT becomes vital for energy and transportation investment planning.

Improvement in automobile fuel economy has been proven to be one of the most effective policies in controlling oil demand and GHG emissions in transportation sector...
around the world (An and Sauer 2004). Conversely, increase of fuel efficiency also raises some concerns about potential negative effects on fuel tax revenue. However, this is a favorable trend for the environment and energy security. Over the past sixty years, the fuel tax has been the primary funding source for building and maintaining highway infrastructure in the U.S. Similar to other parts of the country, Washington State is concerned about rising construction and maintenance costs and declining fuel tax revenue. The last increase in Federal fuel taxes was in 1993. Since then, highway construction costs have risen substantially. The increase of Inflation in both construction and maintenance also have contributed to the highway revenue needs gap. Fuel-efficient vehicles results in less fuel consumption per mile traveled which means fewer tax dollars for the same amount of road use. Despite the negative impact on fuel tax revenue, this trend is favorable for the environment and energy security. Due to importance of economical and environmental issues on society, understanding various potential outcomes of fuel efficiency improvement is vital for governments. Analysis of the effects of fuel efficiency improvement on revenue and emissions is not possible without considering the behavior of fuel consumption.

Besides the effect of fuel efficiency on fuel consumption reduction, higher fuel efficiency reduces the cost of travel, thereby encouraging drivers to drive more, which in turn increases the gasoline consumption. The efficiency improvement offsets some of the energy-saving benefit and creates the rebound effect. Therefore, in order to estimate the future fuel tax revenue and GHG emissions, the rebound effect should be considered.
Promoting usage of electric vehicles (EV) as one of the alternative fuel vehicles is another solution to reduce fuel consumption and GHG emissions. Electric vehicle as one of the green vehicles is more environmentally friendly than the traditional petroleum combustion engine vehicles. Less driving cost and greenhouse gas emissions are two of the important advantages of EV over conventional vehicles and other alternative fuel vehicles. The well-to-wheel efficiency of electric cars is around 1.15 kilometer per million Joule (kn/mJ), while the efficiency is estimated around 0.56 km/mJ for celebrated hybrid model (Toyota Prius) and much lower rate for conventional cars (Toyota Camry, 0.28 km/mJ) (Eberhard and Tarpening 2006; Romm 2006; Nie and Ghamami 2013). In addition, the electric cars have zero local emission at the point of operation and low global emissions; therefore, increasing the use of electric vehicles contributes to reduction of air pollution significantly.

Research Objectives and Anticipated Contributions

The core of this research is to conduct the feasibility and efficiency of policies and their effects on key transportation parameters based on econometric modeling. The major question on which this research focuses is: “How do fuel efficiency improvement, natural gas vehicles and electric vehicles affect key transportation parameters?” Modeling is accomplished in support of the Washington State Department of Transportation. Addressing this question effectively requires the ability to investigate the following issues:

1- What will be the adoption rates of natural gas vehicles?
Research is conducted to evaluate the potential of compressed natural gas vehicles (CNG) to be an economically viable fuel for passenger vehicles in the Washington States. Modeling is performed to estimate the likelihood of consumers and businesses, changing from traditional petroleum fueled vehicles to CNG fueled vehicles. Despite cost advantage of CNG over petroleum, various economic and technical factors prevent widespread adoption of CNG vehicles. In this research the CNG adoption rate is calculated solely based on financial comparison between CNG and conventional vehicles.

Interestingly, contribution of this part of this research is very important in the car manufacturer industries, which have dominant impact on increasing the adopting rate of natural gas vehicles by producing with lower price and higher technology. The CNG vehicle’s price is introduced as a difficulty factor in the vehicles adoption. In order to attract more users, improvement of natural gas vehicles market to distribute in fewer prices is substantial. In manufacturer’s point of view, the role of CNG vehicle fuel tank capacity on increasing commuters’ satisfaction to use natural gas instead of conventional vehicles is presented.

2- What is the impact of natural gas vehicles on VMT?

Understanding the sensitivity of vehicle miles traveled to changes in the adoption rate of natural gas vehicles has important implications for policy makers. CNG vehicles can reduce fuel consumption; however, they may increase the VMT and congestion based on their lower fuel price. The VMT increment as a negative aspect can offset the benefits of expanding the usage of CNG vehicles. In this part the relationship between automobile use and the fuel price of conventional and CNG vehicles is examined.
Considering the fact that natural gas vehicles with fewer fuel prices induce more travel millage is vital in forecasting the VMT. The research is expected to give DOT operational implication about future of VMT and required capacity to service the travel demand. VMT is a suitable measure of the required infrastructure in future.

3- What is the impact of higher fuel efficiency on vehicle emissions and fuel tax revenue?

Considering the effect of fuel efficiency improvement on fuel consumption, the positive and negative influences are analyzed. The positive outcome is reduction of GHG emissions and the negative one is loss of fuel tax revenue. In this section the new rate of fuel tax to keep the fuel tax revenue constant is estimated.

Results of this part of the study contribute to inform governments about potential loss of revenue. Furthermore, it is an important issue to investigate how fuel tax per gallon should be raised to restitute the lost revenue resulted by fuel efficiency improvement. However fuel consumption reduction brings some concerns on revenue, it has positive impact on reducing GHG emissions. Another contribution of this research has environmental implications. It helps environmental agencies to predict future of GHG emissions as result of different policies. In this study effect of fuel efficiency improvement on GHG reduction especially CO₂ is estimated.

4- What are the effective factors on electric vehicles adoption?

In order to answer this question, the significance and the strength of provided incentives and other socioeconomic factors in promoting EV adoption is examined.
Knowing the sensitivity of EV adoption with respect to different factors helps to forecast the use of EV.

Federal and states agencies offer lots of incentives to encourage people to use of electric vehicles. Knowing sensitivity of EV adoption with respect to different factors helps to forecast the use of EV and contributes to the government decision on providing incentives for EV users.

Research Outline

The remaining chapters contained in this document are organized as follows:

Chapter 2- Literature Review
Chapter 3- Simple economic on natural gas vehicles adoption
Chapter 4- Forecasting VMT affected by natural gas vehicles
Chapter 5- Impact of fuel efficiency on revenue and GHG Emission
Chapter 6- Future of electric vehicles
Chapter 7- Conclusion

References


CHAPTER 2
LITERATURE REVIEW

The purpose of this chapter is to review the state of the art in the analysis of technology improvement on key parameters of transportation. Discussion on the natural gas vehicles as an alternative fuel vehicle, VMT forecasting, rebound effect estimation, outcomes of fuel efficiency improvement, and electric vehicles are presented.

Natural Gas Vehicles

According to the Natural Gas Vehicle Association of America, currently there are an approximate 120,000 natural gas vehicles in the U.S. fleet and 15.2 million natural gas vehicles worldwide. The Department of Energy reports that there are 519 public Compressed Natural Gas (CNG) stations in the United States and a total of 1,107 stations including the private stations.

Natural gas has been applied to a wide range of vehicles, including passenger cars, heavy-duty trucks, garbage trucks, three-wheelers (primarily in Asian countries), and buses (Yeh 2007). Yeh (2007) summarized the principal factors that motivate governments to promote the adoption of natural gas as: environmental benefits of reducing local air pollution, availability of natural gas resources and existing pipeline and delivery infrastructure, reduction of dependency on imported oil.

Goyal and Sidhartha (2003) on the air quality of Delhi, summarized the advantageous of natural gas vehicles as: lesser running cost, easier on the engine, longer service life and lower maintenance costs, reducing the demand for finite petroleum
supply, reduction of carbon monoxide emission by over 90%, reduction of carbon monoxide emission by over 90%, improving fuel consumption and engine efficiency, saving on oil filters and oil chargers, lower maintenance cost, reduction in engine noise levels, and reduction in air toxic emission impact by 90%.

Recently, improved drilling technology has increased natural gas production in the United States (Paltsev et al. 2011), causing the supply of natural gas in the United States to grow substantially between now and 2050.

Deal (2012) focused on the viability of CNG-powered heavy duty trucks. He defined some factors that limit the growth of CNG heavy duty vehicles, including: limited refueling infrastructure, high cost of natural gas trucks, high capital costs associated with upgrading a maintenance shop to deal with CNG vehicles, limited operational range due to capacity constraints of CNG fuel tanks, and added weight to the truck. He also noted that the use of liquid natural gas (LNG) is limited to situations where trucks are re-fueled every 1-2 days. Furthermore, he recognized that some fleet operators are apprehensive about adopting new “high risk” technology.

Generally, based on the advantages of natural gas vehicles on environment and cost, they can compete with conventional fuel vehicles. Small and Kazimi (1995) investigated the benefits of using and switching to alternative fuel vehicles. They found the CNG and methanol fuel vehicles more effective based on the assumptions regarding their range, price and performance.

Moniz (2011) and National Petroleum Council (2012) both found that fuel price is the most attractive feature of CNG vehicles. These studies also indicated that the high
vehicle purchase price is prohibitive, even when CNG refueling infrastructure is widespread and if automakers offer more CNG models. Whyatt (2010) examined the incentives and barriers for adopting compressed natural gas (CNG) as a fuel for light-duty passenger cars, heavy duty combination trucks, and fleet vehicles of all types. In all cases the primary incentive to switch from gasoline or diesel to natural gas is the potential fuel cost savings. Li et al. (2009) considered the effect of fuel price on fleet fuel economy. Their results show that high gasoline prices affect fleet fuel economy through two channels: shifting new auto purchases towards more fuel-efficient vehicles, and speeding the scrappage of older, less fuel-efficient vehicles. Davies et al. (2005) investigated the uncertainty associated with the greenhouse gas (GHG) benefits of heavy-duty natural gas vehicles by producing new exhaust emission factors for carbon dioxide (CO2) and methane (CH4) from different heavy duty compressed natural gas (CNG) and liquefied natural gas (LNG) vehicle applications.

In another study on NGV adoption patterns, Yeh (2007) examined that for wide adoption of NGVs beyond fleet vehicles and buses in eight case-study countries (Argentina, Brazil, China, India, Italy, New Zealand, Pakistan, and the US), retail natural gas fuel prices should be kept 40–50% below gasoline and diesel prices, and incentives should be provided sufficiently to keep the payback period at 3–4 years or less.

Dagsvik et al. (2002) analyzed the potential demand for liquid propane gas and electric powered vehicles in addition to dual-fuel vehicles. They applied probabilistic choice models to a stated preference survey of Norway and found purchase price,
kilometers (km) driven, suitable infrastructure for maintenance and refueling as important attributes of alternative fuel vehicles adoption.

Stoneman and Battisti (2000) studied the choice of alternative fuel vehicles under regulations in which economic incentives are available to manufacturers and consumers to produce and choice, respectively. They found that where a regulation favoring the use of the cleaner fuel the price incentives is less effective.

VMT Modeling

VMT as a measure of highway travel can indicate the required investment for highway infrastructure. A number of studies have focused on VMT and the factors that influence VMT. The primary goal of the VMT modeling in this study is to analyze the influence of the presence of natural gas vehicles on travel demand (VMT). Natural gas price is lower than gasoline price, this advantageous might encourage natural gas vehicles owner to drive more. Therefore, the elasticity of VMT with respect to fuel price should be investigated. The elasticity of VMT with respect to fuel cost has been extensively studied; however, the fuel price elasticity of VMT is a less explored topic.

Many studies (e.g., Blair et al. 1984; Dahl and Sterner 1991a; Espey 1998; Goodwin et al. 2004; Haughton and Sarkar 1996; Johansson and Schipper 1997; Oum et al. 1992; Small and Van Dender 2007) estimated the VMT elasticity with respect to fuel cost. The logic behind the elasticity of VMT with respect to fuel cost is that the rational users should respond to fuel cost variation uniformly regardless the source of variation,
whether it is a change in fuel price or in fuel efficiency. In reality, people may not behave uniformly in response to a change in fuel price versus a change in fuel efficiency.

Drollas (1984) surveyed different modeling techniques to estimate price elasticity, including static cross-sectional specification, time-series, and panel data models. The study found that the long-run price elasticity of demand is around -0.8. Sterner and Dahl (1992) tried to stratify a wide variety of previous studies by types of models and data for OECD countries over the period of 1960-1985 and obtain averages of elasticities on each category. Their results show a great degree of difference in the short- and long-run price elasticities. The short run and long run price elasticities of gasoline demand range from -0.1 to -0.24 and -0.54 to -0.96, respectively. Averaging these estimates gives a short run value of -0.23 and a long run value of almost three and a half times as large, -0.77. Using the 2001 National Household Travel Survey (NHTS) data, Puller and Greening (1999) estimated that the elasticity of VMT with respect to fuel price equals to -0.69 based on non-business gas consumptions and miles traveled. Using the nationwide data, Greene et al. (1999) developed a model to investigate the relationship among fuel price, income, and VMT. The author indicated that an increase in income contributes to an increase in VMT while an increase in fuel prices decreases VMT. Liddle (2009) examined the effect of different factors on VMT using data from 1936 to 2004. According to this study, travel demand increased with income while the increases in fuel prices resulted in decreases in fuel consumption.

Wang and Chen (2013) analyzed the effect of fuel price on travel demand for different income groups. They defined five income groups and numbered them from low
to high based on their income levels. For the lowest income group, the estimated elasticity is -0.24. For the second and third groups, the elasticities are insignificant. Elasticities for the fourth and fifth income groups are significant and their values are -0.4 and -0.35, respectively.

One study in the State of Washington was conducted by a workgroup convened by the Washington State Department of Transportation to forecast the statewide VMT (Washington State Department of Transportation 2010). The study developed a VMT model as a function of motorized registration, employment and gas price in Washington State using yearly data. However, both the effect of population growth and the effect of alternative fuel vehicles on VMT forecasting were ignored.

There is doubt that population growth is dominant factor on VMT. Noland (2001) used cross-sectional time series of 50 US states from 1984-1996, to examine the effect of population, income, and fuel price. He found that the effect of elasticity of VMT with respect to population and income is much higher than fuel price. The National Surface Transportation Policy and Revenue Study Commission (2007a) studied trends of VMT and travel demand according to population and income. The specified growth rate of VMT is much higher than the growing rate of population. The National Surface Transportation Policy and Revenue Study Commission (2007b) found that the most important factor affecting travel demand over time is population and its projected growth. According to the study by Polzin et al. (2004) on the 2001 NHTS data, population growth is a significant but not dominant factor for VMT growth. This result is interesting
because it contradicts other studies that consider population as the dominant factor for VMT growth.

Rebound Effect

The key concepts of this part are elasticities of fuel consumption with respect to fuel efficiency and the rebound effect. Numerous econometric models have been developed to estimate the fuel price and fuel efficiency elasticity of fuel consumption. Some empirical studies on fuel consumption elasticity use aggregate time-series data and some rely on pooled cross sectional time-series data. Another categorical issue is model structure, which is single equation or system of equation.

Blair et al. (1984) used monthly aggregate data of Florida from 1967 to 1976 and estimated the impact of fuel efficiency on gasoline consumption. Ordinary least squares (OLS) and general least squares (GLS) methods were used to estimate recursive system of equation model coefficients. Their estimated rebound effect is 30%. Mayo and Mathis (1988) used U.S. aggregate data over the period of 1958-1984 and formulated a recursive dynamic system of equation model. Using the 3SLS method, their calculated rebound effects are 22% and 26% in the short and long run, respectively. Gately (1992) used aggregate data of both cars and light trucks for the period of 1966-1988. The estimated rebound effect is 9% for both short and long run. Greene (1992) developed a linear single VMT model to estimate the fuel efficiency elasticity of fuel consumption and rebound effect. Using the aggregate annual U.S. data for 1957 to 1989, he estimated that both short and long run rebound effects are between 5% and 15%, with the best estimate of
12.7%. The results were based on the model developed using lagged values of VMT to release autocorrelation. Jones (1993) used Greene’s data with additional observations of 1990. The model structures adopted were single static and dynamic of linear and log-linear functional forms. The long-run rebound effect was found to be twice as large as the short-run estimation (roughly 30% vs. 13%). Schimek (1996) used the U.S. aggregate data from 1950 to 1994, and adopted a recursive structure model in double-log form. It is showed that the single-equation results are inevitably subject to the endogeneity bias. This occurs when explanatory variables in a single equation are actually endogenous to the system of interest rather than exogenous. The short- and long-run rebound effects were estimated to be 5-7% and 21-29%, respectively.

Small and Van Dender (2007) modeled the fuel efficiency as an endogenous variable. Their investigation on rebound effect demonstrated 4.5% and 22% fuel saving offset in short-run and in long-run, respectively. In another study, Mayo and Mathis (1988) estimated the effect of fuel efficiency and fuel price on fuel consumption. Their model was a system of equations with fuel efficiency as the endogenous variable. They found rebound effects of 22% and 26% in short-run and in long-run, respectively.

By reviewing different studies, it is concluded that the model structure and estimation techniques are critical in analysis of the rebound effect as well as fuel consumption. Based on literature reviews done by De Jong and Gunn (2001), Graham and Glaister (2002) and Goodwin et al. (2004), short-run rebound effects are reported to be 10-20%. Therefore, 14% short-run rebound effect estimated in this study complies with results from previous studies. In this study the system of equations model is
estimated using 3SLS method to achieve unbiased and consistent results. Furthermore, the autoregressive model is used to release the effect of autocorrelation of each model residuals. The order of autoregression is obtained by conducting tests on each single equation.

Policies on Fuel Consumption Reduction

The significant parts of greenhouse gas emissions and petroleum consumption are resulted from motor vehicles use. Consequently, most analysts believe that addressing climate change and energy dependency requires strategies focusing on the transportation sector.

A number of countries installed the corporate average fuel economy (CAFÉ) regulation as an instrument to reduce fuel consumptions and GHG emissions. There are numerous researches that investigate the effects and efficiency of CAFÉ policy. Greene and Duleep (1993) concluded that the most important effects of CAFÉ are the reliability of supply on the international oil market and reduction of air pollutants. Harrington (1997) investigated the relation between fuel economy and emissions. He used the remote sensing data on emissions for different vehicle types and fuel economy data. He found that the better the fuel economy, the lower the emissions.

Goldberg (1998) estimated the effects of CAFE standards on the fuel economy of the new car fleet. According to this study, 1989 CAFE standard caused a profit loss of around $210 million for domestic manufacturers. This suggested that CAFE should provide incentives for manufacturers to develop more fuel-efficient vehicles.
Austin and Dinan (2005) studied energy security and climate change. They showed gasoline consumption reduces by increasing corporate average fuel-economy (CAFE) standards. Kleit (2004) analyzed the effect of increasing the fuel efficiency by 3.0 MPG and found that it imposes additional costs over $4 billion per year and reduces gasoline consumption by about 7% per year.

Besides the positive impact of fuel efficiency improvement on fuel consumption and GHG emission reduction, higher efficiency also reduces the fuel tax revenue. While there have been many studies on different impacts of fuel tax increment, in this study the effect of fuel efficiency improvement on fuel tax is investigated.

There are three principal transport revenue options (Huang et al. 2010): user charges based on fuel consumption, user charges based on distance traveled, and user charges based on congestion. The fuel consumption-based taxes are the principal revenue stream from the transportation sector. The in place collection mechanism is easy and relatively inexpensive. In addition, fuel tax is effectively a carbon tax because a vehicle carbon dioxide is directly related to the amount of fuel burned.

There has been a debate over the appropriate level of gasoline taxation in the U.S. every few years. Increasing the tax rate might be beneficial based on Ramsey rule, which points to higher tax rate on goods and services that have relatively inelastic demand (Haughton and Sarkar 1996). In literature review, there have been numerous studies on impacts of increase gasoline tax policy on key parameters of transportation. Some studies examined the influence of gasoline taxes on gasoline demand as a function of gasoline price. For example, Dahl and Sterner (1991a, 1991b) found the price elasticities
of gasoline consumption ranging from -0.07 to -1.05, with most estimates of long-run elasticities clustering in the range of -0.5 to -0.6. Another survey by Goodwin (1992) found short-run elasticities of -0.27, and long-run ones around -0.71 to -0.84. Dahl (1995) found long-run price elasticities ranging from -0.7 to -1.0 and Graham and Glaister (2002) found slightly lower values between -0.6 and -1.0. Li et al. (2009) investigated the effect of increasing gasoline price on fuel efficiency, and estimated that 10% increase in gasoline prices from 2005 levels will generate 0.22% increase in fleet fuel economy in the short run and 2.04% increase in the long run. Bento et al. (2009) examined the impacts of increased U.S. gasoline taxes. They found that each cent-per-gallon increase in the price of gasoline reduces the equilibrium gasoline consumption by about 0.2% that is equal to $30 per year revenue for the average household.

West and Williams (2005) investigated the distributional impact of gasoline taxes, and suggested the optimal gasoline tax. They specified that the gas tax increases the fuel efficiency and decreases the mile driven.

Electric Vehicles

In order to increase the sustainability of transportation system, reduction of GHG emissions, air pollution and dependence on fossil fuels is necessary. Electric vehicles are one possible innovation to help address the environmental and energy dependency concerns. In the U.S., large deployment of EVs can play a significant role in addressing some of these problems (Natural Resources Defense Council 2007). However, EV is heavily dependent on some external factors such as stringent emissions regulations, rising
fuel prices, or financial incentives (Eppstein et al. 2011). The U.S. government provides stimulus funding in order to extend the use of alternative fuel vehicles (Skerlos and Winebrake 2010). In order to achieve the goal of having one million electric vehicles on the U.S. roads by 2015, the American Recovery and Reinvestment Act (ARRA) (U.S. Congress 2009) allocates over $2 billion to electric vehicles and battery technology.

Referring to the study done by Tseng et al. (2013), EVs are more environmentally friendly vehicles with low GHG emissions and tailpipe air pollutants emissions. Moreover, their energy conversion is more efficient compared to conventional internal combustion engines (ICEs).

However, due to some significant barriers, EV represents a small market share of vehicles in service. EVs have short driving range, long recharge time, high battery cost, and heavier curb weight. Axsen et al. (2010) suggested that battery technology limitations and high battery cost are the major obstacles to widespread adoption of EVs. Battery cost is a determinant factor in the economic viability of EVs especially PHEVs and BEVs. Cost of advanced batteries is estimated between $800 to $1000/kW h (Pesaran et al. 2007). Energy storage is another fundamental technological constraints to the commercialization of EVs (Mandel 2007). One of the key goals of the U.S. Department of Energy (DOE 2010) is to reduce the cost of high-energy, high-power batteries from $1200/kW h in 2008 to $300/kW h by 2014 to enable cost-competitiveness of PHEVs.

Besides the technological problem mentioned above, social issues are other challenging factors that should to be considered in order to achieve commercial success of EVs. Ozaki and Sevastyanova (2011) determined that consumer acceptance is crucial
to continuing success of sustainable transportation. Diamond (2009) summarized some common barriers to the adoption of any new technology as; lack of knowledge by potential adopters, high initial costs and low tolerance risk. The study by Hidrue et al. (2011) identified the level of education, income, and environmentalism as consumer characteristics with positive effect on EV adoption. Fuel price have been introduced as one of the influential predictors of EV diffusion in agent-based models (Eppstein et al. 2011; Shafiei et al. 2012). The combination of fuel price and electricity price as the majority of EV operation expenses are positively correlated to likelihood of EV adoption (Zubaryeva et al. 2012). In some studies (Egbue and Long 2012; Struben and Sterman 2008; Tran et al. 2012; Yeh 2007;) availability of charging infrastructures has been identified as an important criteria in consumer acceptance of alternative fuel vehicles. Several factors considered in different studies as influential factors on EV adoption rate include: level of urban density, vehicle diversity, local involvement, and public visibility (Eppstein et al. 2011; IEA 2011; IEA 2013; Sierzchula et al. 2014; Van den Bergh et al. 2006).

Different researchers used different methods for modeling the effects of various factors on alternative fuel vehicles adoption rates. Sierzchula et al. (2014) used multiple linear regression analysis in order to examine the relationship between different socio-economic variables and 30 national electric vehicle market shares for the year 2012. Accordingly, financial incentives, charging station, and local involvement were defined as the most significant factors. Egbue and Long (2012) investigated potential socio-economic and technological barriers on consumer adoption of EVs and determined how
consumer decision making on EV adoption is effected by sustainability issues. They used an internet-based survey from a sample population in order to data collection. Their methodology was based on the chi-square data analysis to investigate differences in perceptions and attitudes among the sample population.

The methodology developed in this dissertation is based on panel data over 19 states of the U.S. with no missing data for selected variables. In addition, based on the availability of data, the aggregated market share model is performed to present different dominant factors on EV adoption.

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CHAPTER 3

QUANTITATIVE EVALUATION of CNG VEHICLE OWNERSHIP PATTERN: AN ECONOMIC-BASED APPROACH

Abstract

Increasing concerns about energy dependence, air quality and emission, and more recently climate change have led to interest in development of natural gas vehicles. The major advantage of natural gas vehicles compared to gasoline vehicles is their lower fuel cost. However, several economical and technical factors such as limited range and limited availability of the related infrastructure prevent widespread adoption of natural gas vehicles. This paper offers a model of adoption of compressed natural gas (CNG) vehicles. This model evaluates if CNG can be an economically viable fuel option for passenger vehicles in the United States. The results indicate that the percentage of commuters that adopt CNG is very small even if CNG fueling infrastructures were fully developed and CNG vehicles were widely available for purchase. More vehicle miles traveled (VMT) and higher fuel price differential encourage commuters to adopt CNG vehicles, while higher fuel efficiency and more purchase price differential, results in lower adoption rate. In this study, it is demonstrated that in some cases depending on the values of the model’s parameters, some of the commuters purchase a CNG vehicle as their second car, in addition to a regular gasoline-powered car.
Introduction

Natural gas has the potential to be an attractive substitute for petroleum in the automobile fuel market. One of the principal factors that motivates governments to widespread the adoption of CNG vehicles is environmental benefits of reducing local air pollution. More usage of CNG vehicles over diesel and gasoline vehicles reduces the emission levels of non-methane organic gases/reactive organic gases (NMOG/ROG), nitrogen oxides ($NO_x$), carbon monoxide (CO), and air toxics, as well as, cold-start emission, off-cycle emissions, evaporate emissions, and running-loss emissions (Goyal and Sidhartha 2003; Nylund and Lawson 2000). These benefits make the CNG attractive particularly where local urban air quality is poor and environmental issues are a concern.

Recently, improved drilling technology has increased natural gas production in the United States. Higher natural gas production caused a significant decrease in its price (Paltsev et al. 2011). Natural gas prices in the U.S. have fallen more than sixty percent from their peak in 2008 (Paltsev et al. 2011; Staub 2013). The increasing price of petroleum and decreasing price of natural gas, at British Thermal Unit (BTU) parity quantities, means natural gas has a growing cost advantage. Natural gas is also attractive for its high thermal efficiency. Accordingly, the Energy Information Administration expects natural gas to be the fastest growing fossil fuel in the world through 2035 (EIA 2012).

Despite cost advantage and reduced emissions of natural gas, in comparison to other sectors of the U.S. economy, the transportation sector does not use natural gas to meet its energy needs (Paltsev, et al. 2011). Lack of refueling infrastructure, high
incremental price of natural gas vehicles, and limited CNG power trains offered by automakers have historically suppressed the demand for CNG vehicles (National Petroleum Council 2012). CNG vehicles are more expensive than gasoline-powered vehicles, partly due to the cost of building fuel systems capable of handling a compressed gaseous fuel. These added expenses have resulted in low supply of CNG vehicles, which in turn, contributed to limited fueling infrastructures.

The disadvantages associated with the engineering requirements for CNG fuel tanks include: reduced vehicle range, increased fueling frequency, increased vehicle weight due to heavy fuel tanks capable of safely storing compressed fuel, and reduced storage space. Additionally, CNG vehicles are typically less powerful due to the lower energy density of natural gas compared to gasoline vehicles (Werpy et al. 2010; Whyatt 2010).

According to the Natural Gas Vehicle Association of America, currently there are approximately 120,000 natural gas vehicles (NGV) in the U.S. fleet and 15.2 million NGVs worldwide. The Department of Energy reports that 519 public CNG stations and a total of 1,107 stations including the private stations exist in the United States. Due to few CNG passenger vehicles marketed in the United States, considerable uncertainty regarding the premium price of a CNG vehicle is observed. The limited information available suggests that the CNG premium price has not decreased over time. Furthermore, higher manufacturing volume may not result in lower costs (Walls 1996).

Regarding the attractions and barriers of natural gas vehicles, Deal (2012) focused on the viability of CNG-powered heavy duty trucks. He determined some factors that
limit the growth of CNG heavy duty vehicles: limited refueling infrastructure, the high cost of natural gas trucks, costs of upgrading a maintenance shop to deal with CNG vehicles, limited trip range, high weight of tank. He also noted that usage of liquid natural gas (LNG) is limited to cases where trucks are re-fueled every 1-2 days. Furthermore, he recognized that some fleet operators are apprehensive about adopting new “high risk” technology. Moniz (2011) and the National Petroleum Council (2012) both found that fuel price is the most attractive feature of a CNG vehicle. These studies also indicated that even when CNG refueling infrastructure is wide-spread and even if automakers offer more CNG models, the high vehicle purchase price is prohibitive factor. Whyatt (2010) examined the incentives and barriers for adopting compressed natural gas (CNG) as a fuel for light-duty passenger cars, heavy duty combination trucks, and fleet vehicles of all types. In all cases the primary incentive to switch from gasoline or diesel to natural gas is the potential fuel cost savings. Davies et al. (2005) investigated the uncertainty associated with the benefits of greenhouse gas (GHG) emissions reduction related to heavy-duty natural gas vehicles. They introduced new exhaust emission factors for carbon dioxide (CO2) and methane (CH4) from application of different heavy duty compressed natural gas (CNG) and liquefied natural gas (LNG) vehicles.

The approach in this study is based on a decision making model which assumes that commuters live at varying distances from work and leisure (or shopping) destinations and use personal vehicles for both work and shopping needs. While all commuters are assumed to live within CNG car’s range for their work travels, some live too far from their shopping destination to use a CNG vehicle for all their travel needs.
It is demonstrated that different ownership patterns arise from various model parameters. The principal parameters for this model are: the premium paid for the CNG fueled vehicle, the fuel efficiency of the vehicle (assumed to be the same for both CNG and conventional fuel), and the price differential between CNG and gasoline. These parameters can be used to calculate whether a CNG vehicle or a conventional vehicle is the most financially beneficial vehicle. The model uses this information to predict the adoption rate of CNG vehicles.

The rest of the paper proceeds as follows. Next section presents the details of the financial decision making model. After that, the model analysis and vehicle ownership patterns are discussed. The results of the simulation are presented afterwards, and then results of the sensitivity analysis. At last the conclusion of this research is presented.

Modeling Procedure

The theoretical model assumes a consumer should make a decision between purchasing a conventional or a CNG powered passenger vehicle. This approach restricts the applicability of the results to the light duty vehicle fleet. The consumer makes a decision solely based on the financial properties of each vehicle (Barnes et al. 2014). Spatial modeling to investigate how the consumer’s location affects CNG adoption rates is performed based on the approach by Bilotkach and Mills (2012).

It is assumed that consumers use personal vehicles for all travel purposes, and they never walk or use transit. For spatial modeling, it is assumed that 100 consumers are distributed uniformly along a linear path. Therefore, each consumer is uniquely
identified by his location on the line $x \in [0,100]$. The distance of infrequent trip destinations (leisure/shopping) to CBD is $\alpha < 100$. This model is shown in Figure 3.1.

The most important assumption underlying this analysis is that a CNG vehicle is an available option. CNG vehicles have a shorter range than conventional vehicles. CNG fueling infrastructure is extremely limited in many areas of the United States. Lack of fueling infrastructure combined with the reduced range of CNG vehicles is a serious constraint for most consumers. Moreover, CNG vehicle choices are extremely limited. In this study, consumers are not limited to the mentioned constraints when making vehicle purchase decisions.

It is assumed that the CNG single trip range is: $200 < d < 2(100 + \alpha)$. This assumption implies that all consumers are located within a CNG vehicle’s range for their work trips, while for some consumers CNG is not a viable option for leisure/shopping trips. Furthermore, consumers located between CBD and $k = \frac{d}{2} - \alpha$ are able to use CNG for all their travel needs, while consumers living between $k$ and 100 points need to use their regular vehicle, at least for shopping and leisure trips.

![Figure 3.1 General model setup](image)

It is assumed that a consumer located at point $x$ chooses between two vehicles. A rational consumer will choose the vehicle with lower cost, where cost is measured by the
net present discount value of all cash flows associated with their choice. The expected maintenance costs, registration fees, and other costs associated with normal vehicle ownership are assumed to be the same for both vehicle types. The vehicles differ in the initial purchase price, depreciation costs (due to the purchase price differential), and the fuel cost. The total cost associated with vehicle ownership can be expressed as (Barnes et al. 2014):

\[ T_{C_i} = V_{i0} + f_{i0} + f_{i1}(1+r)^{-1} + f_{i2}(1+r)^{-2} + ... + f_{iT}(1+r)^{-T} - V_{i0} \left(1+\delta\right)^{-T} (1+r)^{-T} \]  

(3.1)

where the subscript \( i \in \{g,c\} \) indicates whether the vehicle is powered by gasoline (g) or CNG (c), \( T_{C_i} \) is the total present discounted value of all costs associated with the vehicle, \( V_{i0} \) is the initial value or the vehicle’s purchase price, \( f_{it} \) is the fuel cost in time period \( t \), and \( r \) represents the individual’s rate of discount. \( T \) is the terminal time period at which the individual sells or scraps the vehicle. The parameter \( \delta \) measures the per-period rate of depreciation; therefore, the last term in the expression captures the sale or scrap value of the vehicle at time \( T \). Assuming similar fuel costs in each time period (\( f_{it}=f_i \) for all \( t \)) this expression can be simplified and written as:

\[ T_{C_i} = \left[ V_{i0} - V_{i0} \left[(1+\delta)(1+r)^{-T}\right] \right] + \sum_{t=0}^{T} (1+r)^{-t} f_i \]  

(3.2)

The expression \( V_{i0}^{*} = [V_{i0} - V_{i0}[(1+\delta)(1+r)]^{-T}] \) is the vehicle purchase cost minus the present discounted value of the terminal vehicle value (scrap or resale value). Therefore, it represents the cost of owning the vehicle for \( T \) periods of time, independent of fuel costs. Equation (3.2) can be rewritten as follows:
It is assumed that within a given time period, a consumer makes \( N \) trips to CBD, and one trip to a leisure/shopping destination; therefore, the consumer travels a distance of \( 2((N + 1)x + \alpha) \) in each time period. Fuel consumption is the ratio of distance travelled (VMT) to fuel efficiency (MPG). Fuel cost \( f_i \) is the price of fuel, \( p_i \), multiplied by fuel consumption, and is given by:

\[
 f_i = \frac{2((N + 1)x + \alpha)p_i}{\text{MPG}_i}
\]  

(3.4)

where \( p_i \) is the price of fuel type \( i \) per gallon and \( \text{MPG}_i \) is fuel efficiency of vehicle type \( i \). Thus, substituting this formula for the total cost in equation (3.3) yields:

\[
 TC_i = V_{i0}^* + \sum_{t=0}^{T} (1 + r)^{-t} \left[ \frac{2((N + 1)x + \alpha)p_i}{\text{MPG}_i} \right]
\]  

(3.5)

Since the gasoline and CNG vehicles are the only two alternatives, the commuter’s choice is determined solely by the difference in total cost of the two vehicles. Consumers choose the alternative with the least total cost. In this study, it is assumed that the consumer’s nominal fuel price and fuel efficiency for each type of vehicle is the same in each period. However, fuel prices may fluctuate and fuel efficiency may also vary due to variations in vehicles size, year and make. It is also assumed that both types of vehicles depreciate at the same rate. This assumption may not be true in practice (Barnes et al. 2014).
Analysis

The consumer’s location is a major factor affecting their decision. There are two groups of consumers: 1- Consumers for which the range of CNG vehicles meets all their needs \((x_1 < k)\), 2- Consumers that are constrained by the range of CNG vehicles \((k < x_2 < 100)\). The first group should decide whether it is financially beneficial to purchase a CNG vehicle. The second group should purchase a gasoline vehicle. However, it might still be more beneficial to purchase a CNG vehicle as their second car for some of their needs.

The point \(k\) from CBD defines a boundary for consumers that can use CNG for both work and leisure trips. The magnitude of \(k\) is related to the single-trip range of CNG and to the distance of leisure/shopping destination from CBD \((\alpha)\).

**Group 1**

Based on the difference in total ownership cost, a rational consumer will choose the CNG powered vehicle if:

\[
\Delta TC = TC_g - TC_c = (V_{g0}^* - V_{c0}^*) + 2 \sum_{t=0}^{T} (1 + r)^{-t} ((N + 1)x_1 + \alpha) \left( \frac{p_g}{MPG_g} - \frac{p_c}{MPG_c} \right) > 0
\]

The minimum distance from CBD for a rational consumer to select a CNG vehicle is defined by simplifying the above equation:

\[
x_1 \geq \frac{(V_{c0}^* - V_{g0}^*) - 2 \sum_{t=0}^{T} \alpha (\frac{p_g}{MPG_g} - \frac{p_c}{MPG_c})(1 + r)^{-t}}{2 \sum_{t=0}^{T} (N + 1)(\frac{p_g}{MPG_g} - \frac{p_c}{MPG_c})(1 + r)^{-t}}
\]
This expression means that consumers located closer than $x_1$ to CBD would not rationally buy a CNG vehicle. The consumers are indifferent between a CNG vehicle and a conventional vehicle on the boundary point $x_1$. These consumers can make up for the premium paid for CNG vehicle by saving on the fuel-costs. However, consumers located at $x_1 > k$ still do not choose a CNG vehicle because of its range limitations.

**Group 2**

For consumers located farther than $k$, a CNG vehicle is not practical because of its range limitations. These consumers must retain their gasoline vehicle but they can decide to buy a CNG vehicle in addition to the gasoline vehicle to split their travel needs between the two vehicles. The CNG vehicle will be used for work trips, while gasoline vehicle will be utilized for leisure trips. Therefore, the total cost of owning both types of vehicles is given by:

$$T_{c_g + c} = V_{g0} + V_{c0} + 2 \sum_{t=0}^{T} (1 + r)^{-t} \left[ \frac{(N x_2) p_c}{MPG_c} + \frac{(x_2 + \alpha) p_g}{MPG_g} \right]$$

(3.8)

Using a similar approach as for group one, the minimum distance of group two to CBD, $x_2$, to make the option of buying a CNG vehicle as a second vehicle financially beneficial is calculated as follows:

$$x_2 \geq \frac{V_{c0}^*}{2 \sum_{t=0}^{T} N \left( \frac{p_g}{MPG_g} - \frac{p_c}{MPG_c} \right)(1 + r)^{-t}}$$

(3.9)

$x_2$ is the location of consumers that are indifferent between having only a gasoline vehicle and purchasing a CNG vehicle as a second car. It means purchasing a CNG
vehicle as second car would be beneficial only for the consumers whose distance to CBD is more than $x_2$. If $x_2 \leq k$, all commuters living outside of the CNG range in the interval of $(k, 100]$ will purchase a CNG vehicle as their second car. On the other hand, when $x_2 > 100$, no one will buy a CNG vehicle as second car. If $k \leq x_2 \leq 100$, then commuters located between point $k$ and $x_2$ will not adopt CNG car, while those located between $x_2$ and 100 will. It is interesting that distance to the leisure destinations and the initial prices of gasoline vehicles do not affect equation (3.9). This fact reflects that the choice to use a gasoline vehicle for leisure trips is predetermined.

**Vehicle ownership patterns**

Based on the model developed, the probability of purchasing a CNG vehicle as the only car owned by commuters of group one ($P_1$) and the probability of buying a CNG vehicle as the second car owned by commuters of group two ($P_2$) are calculated and shown below by (Bilotkach and Mills 2012):

\[
P_1 = \max\{0, \min\{k - x_1, k\}\} \quad (3.10)
\]
\[
P_2 = \max\{0, \min\{100 - k, 100 - x_2\}\} \quad (3.11)
\]

By considering different values for model’s parameters, six different cases for CNG vehicle ownership are defined. In each case the adoption rate of CNG vehicles is determined as by (Bilotkach and Mills 2012):

\[
S_c = P_1 + P_2 \quad (3.12)
\]

**Case 1:** $x_1 > k; x_2 > 100$. 

In this case consumers fail to adopt a CNG vehicle, \( P_1 = 0 \), \( P_2 = 0 \), \( S_c = 0 \) (Figure 3.2-a).

Case 2: \( x_1 \leq 0 \); \( x_2 \leq k \).

In this case all the consumers adopt a CNG vehicle. All commuters located within CNG range buy CNG instead of a regular car, whereas people living outside the CNG range buy a CNG car as their second vehicle. Clearly, \( P_1 = k \), \( P_2 = 100 - k \), \( S_c = 100 \) (Figure 3.2-b).

Case 3: \( x_1 > k \); \( k \leq x_2 \leq 100 \).

In this case none of the consumers that live within the CNG vehicle’s range adopt a CNG vehicle, whereas some or all of the consumers living outside of the CNG vehicle’s range purchase a CNG as their second car. In this case: \( P_1 = 0 \), \( P_2 = 100 - x_2 \), \( S_c = 100 - x_2 \) (Figure 3.2-c).

Case 4: \( 0 < x_1 \leq k \); \( 100 < x_2 \).

In this case some of the consumers living within the CNG vehicle’s range adopt CNG vehicles instead of gasoline vehicles, but none of the commuters located outside the CNG vehicle’s range adopt CNG as a second vehicle. In this case: \( P_1 = k - x_1 \), \( P_2 = 0 \), \( S_c = k - x_1 \) (Figure 3.2-d).

Case 5: \( 0 < x_1 \leq k \); \( x_2 \leq k \).

For case 5, all the consumers living outside the CNG vehicle’s range adopt CNG in addition to a gasoline vehicle. The consumers living within the CNG vehicle’s range
partially adopt CNG vehicles. In this case: \( P_1 = k - x_1 \), \( P_2 = 100 - k \), \( S_c = 100 - x_1 \). Therefore, only the consumers that live within \( 0 < x < x_1 \) do not adopt a CNG vehicle (Figure 3.2-e).

**Case 6:** \( 0 < x_1 \leq k; k < x_2 \leq 100 \).

Commuters inside and outside of the CNG vehicle’s range partially adopt CNG in case 6. In this case: \( P_1 = k - x_1 \), \( P_2 = 100 - x_2 \), \( S_c = 100 + k - x_1 - x_2 \) (Figure 3.2-f).

**Simulation**

There are many factors that affect the consumer’s vehicle ownership pattern. In order to predict vehicle type choice for a given consumer, the model requires estimation of \( V_{g0}, V_{c0}, p_g, p_c, MPG_g, MPG_c, T, r, \) and \( \delta \). If a consumer knows the value of these parameters, it is straightforward to calculate the present discounted value of the total cost for each type of vehicle and make the appropriate decision. Using the present value of total cost, the model simulates the minimum distance to CBD for both commuters located inside \( (x_1) \) and outside \( (x_2) \) of the CNG vehicle’s range, and calculates the adoption rate.

The simulation results are derived based on assumptions of consumer total cost minimization (as discussed above) and, more importantly, availability of vehicle supply and infrastructure and similarity of fuel efficiency for both vehicles fuel systems. Baseline parameter values assumed in this study are: depreciation rate = 15\%, discount rate = 6\%, the expected length of vehicle ownership = 60 months (current average of Kelly Blue Book), \( N = 30 \), \( \alpha = 40 \), \( d = 200 \), \( k = 60 \), and \( MPG = 25 \). The simulation
is done based on changing the purchase price and the fuel price differential (the difference between the gallon-equivalent price of CNG and the price of gasoline).

Table 3.1 presents how the minimum distance to CBD for commuters group one ($x_1$) varies with fuel price differential and the vehicle price differential considering the baseline parameters. As shown in Table 3.1, the minimum distance to CBD increases by increasing the purchase price differential and decreasing the fuel price differential. The results demonstrate that the consumers located farther from CBD are more likely to adopt a CNG vehicle even when the vehicle price differential is large and the fuel price differential is small. These consumers can recover the high purchase price differential with savings on fuel costs.

In the cases that $x_1$ is less than $k = 60$, commuters of group one located between $x_1$ and $k$ adopt a CNG vehicle (cases 4, 5, and 6). For those that $x_1$ is father than $k = 60$, adoption rate is zero (cases 1 and 3). For instance for the fuel price differential of $2.00, and a purchase price differential of $4000, the consumers between points 44.06 and 60 adopt a CNG car instead of a gasoline car for all purposes. This would imply a 15.94% primary vehicle adoption rate.
Figure 3.2 Car ownership pattern in cases 1 to 6
Table 3.1 Minimum distance to CBD for commuters group one ($x_1$)

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<td>14.35</td>
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<tr>
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<td>13.83</td>
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Table 3.2 presents variation of adoption rate with respect to the fuel price differential and the vehicle price differential for group one. Increasing the fuel price differential and decreasing the purchase price differential results in higher primary adoption rate. However, the purchase price has a much stronger impact on adoption rate than the fuel price. For example, if the purchase price differential is $6000, and the fuel price differential is $2.20, then increasing the fuel price differential to $2.30 would raise adoption rate to 2.13%. On the other hand, decreasing the purchase price differential to $5000 would raise the adoption rate to 9.75%.

As mentioned before, the minimum distance of commuters group two that live outside of CNG vehicle’s range does not depend on the gasoline vehicle’s price. Table 3.3 shows the predicted distance ($x_2$) with respect to the fuel price differential and the
CNG car’s purchase price. Based on the definition of $x_2$, commuters that live between this point and point 100 adopt a CNG vehicle in addition to their gasoline vehicle. Clearly, the minimum distance of commuters to CBD, for beneficial adoption of CNG as second vehicle increases, as the vehicle price increases. It also decreases as the fuel price differential increases.

The secondary vehicle adoption rates calculated for various CNG vehicle purchase price and fuel price differential are shown in Table 3.4. For CNG vehicle purchase prices greater than $12,000, no consumers would find a secondary CNG vehicle financially advantageous under our baseline parameters. High secondary vehicle adoption rate only occurs under our baseline assumptions when CNG vehicle purchase price is $10,000 and the fuel price differential is at least $2.50.

Table 3.2 Proportion of passenger with CNG as their single car

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Table 3.3 Minimum distance to CBD for commuters group two \((x_2)\)

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Table 3.4 Proportion of passenger with CNG as their second car

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<td>$3.0</td>
<td>31.13%</td>
<td>9.66%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
</tbody>
</table>
Sensitivity Analysis

Sensitivity analysis with analytical methods is a highly effective way to assess the effects of different components in the system. There are many factors that affect the commuters’ decision about adopting a CNG vehicle.

Currently, CNG fueling is extremely limited in many areas of the United States. Accordingly, the single trip range of CNG vehicles affects whether commuters living in different locations consider adopting a CNG vehicle or not. In Figure 3.3, adoption rates of group one estimated for various single trip ranges \((k)\) and different fuel price differentials are presented. The CNG vehicle adoption rate increases as the single trip range increases. CNG vehicles with higher single trip range can be used for more trips; this results in more saving on fuel cost. Fuel price differential has positive effect on CNG adoption rates; this means that increasing the gasoline price and decreasing CNG price encourage people to use CNG vehicles. The slope of CNG vehicle adoption rate over fuel price differential is more for higher CNG trip range. This implies that the magnitude of fuel price effect on CNG adoption rate increases as the single trip range improves.

It is assumed that fuel efficiency is constant across vehicle types. However, this is not a realistic assumption and is unlikely to happen. Improving fuel efficiency leads to lower fuel consumption. However, the literature on the rebound effect indicates that reduction of fuel consumption by improving fuel efficiency appears to be relatively small and declining over time (Gillingham 2010; Greene 1992; Greene, et al. 1999; Jones 1993; Small and Van Dender 2007). Sensitivity analysis of CNG vehicles adoption rate with respect to fuel efficiency, presented in Figure 3.4, demonstrates that higher fuel
efficiency will lead to lower adoption rates. This is explained based on the reduction in the expected fuel cost savings associated with CNG as consumers use less fuel. On the other hand, improved fuel efficiency increases the single trip range and adoption rate of CNG vehicles, which was not considered in this study.

For the commuters of group two, sensitivity analysis of adoption rate with respect to single trip range at various levels of fuel price differential is presented in Figure 3.5. Improving single trip range shifts the boundary point $k$ farther from CBD. Generally, this decreases the percentage of people that adopt a CNG vehicle as their second car, because some of the commuters of group two fall under group one (who use CNG vehicles for all their needs).

![Figure 3.3 Group one CNG vehicle ownership varies by single trip range and fuel price differential](image-url)
Figure 3.4 Group one CNG vehicle ownership varies by single trip range and MPG

Changes of fuel efficiency have the same effect on CNG adoption by commuters of both groups. Fuel efficiency reduction results in greater fuel consumption, which magnifies the fuel cost savings. In addition, considering Figure 3.4 and 3.6, the effect of fuel efficiency on CNG vehicle adoption rate is negligible in low levels of fuel price differential.

Overall, considering results of sensitivity analysis of CNG vehicle adoption rate, the fuel price differential magnifies the effect of other factors. This means that CNG vehicle adoption rate is more sensitive to single trip range and fuel efficiency in higher levels of fuel price differential. However, the results indicate that in higher values of CNG single trip range and fuel efficiency, the sensitivity of the adoption rate is less.
Figure 3.5 Group two CNG vehicle ownership varies by single trip range and fuel price differential

Figure 3.6 Group two CNG vehicle ownership varies by fuel efficiency and fuel price differential
Conclusion

A framework was developed to model CNG vehicle adoption rate considering two different approaches; adoption of CNG car as single vehicle by consumers located inside the CNG vehicle’s leisure trip range, and adoption of CNG vehicles as a second car for consumers outside of that range. The results showed that the proportion of commuters, which are interested in adopting CNG cars is highly dependent on the distance of travel (VMT), natural gas and gasoline price deferential, and CNG and conventional vehicles price differential. These results demonstrate that the consumers located farther from their work are more likely to adopt a CNG vehicle even when the vehicle price differential is large and the fuel price differential is small. Intuitively, these consumers can still recover the high purchase price differential with savings on fuel costs. In situations that VMT is low, the fuel and vehicle price differential are more influential. The high fuel price differential and low vehicle price differential increase the willingness of people to adopt CNG cars.

Moreover, it is indicated that the proportion of the vehicle fleet that would find a CNG fuel system economically advantageous is small. This prediction reflects the current share market. Simulations suggest that a substantial decrease in the vehicle price differential for CNG vehicles is necessary to induce CNG vehicle adoption for a significant portion of the vehicle fleet. Moreover, the model predicts that even with technology improvements that allow for lower conversion costs or lower manufacturer vehicle price differentials, CNG vehicles are likely to remain a minority in the vehicle fleet.
The model predicts that overall CNG vehicle adoption rate will be low. However, higher effective range of CNG vehicles, increased fuel infrastructures, and technology improvement to lower the production cost are some of the factors that lead to more CNG vehicle adoption.

Changes in the vehicle fleet composition and driving habits can affect this analysis. However, as consumers respond to gasoline price increment by driving less and purchasing more fuel-efficient vehicles, the potential gains from CNG vehicle adoption will be diminished. To summarize, the model suggests that CNG is most likely to be cost effective for high mileage users, low MPG vehicles, high gasoline price relative to natural gas, and existence of adequate fuel infrastructure.

References


CHAPTER 4

DO NATURAL GAS VEHICLES CHANGE VEHICLE MILES TRAVELED (VMT)?
AN AGGREGATE TIME SERIES ANALYSIS

Abstract

Understanding the sensitivity of vehicle-miles travelled (VMT) to changes in the adoption rate of natural gas vehicles has important implications for policy makers. This paper examines the relationship between automobile use and share of natural gas vehicles with cheaper fuel price faced by consumers through a case study conducted in Washington State. The automobile use model is estimated using annual time series data from Washington State. The explanatory variables contained within the model are the number of registered vehicles, employment, and fuel price. Additional analysis is performed to exclude the effect of population growth on VMT trend by modeling the VMT per capita. The best fitted model for both VMT and VMT per capita is ARIMA (0,1,1). Future travel is forecasted using models that consider different natural gas vehicles share scenarios. The share of natural gas vehicles is forecasted under various price conditions using a model based on the joint distribution of household VMT and fuel efficiency (MPG) in the 2009 NHTS. Results indicate that in a high adoption rate scenario, in which 60% of the fleet is natural gas vehicles, VMT and VMT per capita at 2031 will have 9% and 19% increment respectively. This implies that NGV adoption is unlikely to have a large influence on aggregated VMT and VMT per capita. Considering sensitivity analysis, natural gas vehicle purchase price has more influence on induced
VMT than fuel price. The results in Washington State are applicable to trends seen nationwide in VMT growth and VMT per capita decline.

Introduction

Natural gas has the potential to become an attractive substitute for petroleum. Natural gas prices in the U.S. have fallen more than sixty percent from their peak in 2008 and proven reserves are approaching all-time high levels (Moniz 2011; Paltsev et al. 2011; Staub 2013). The increasing price for petroleum and decreasing price for natural gas provide a growing cost advantage over gasoline (Barnes et al. 2014). Replacing gasoline-based vehicles with natural gas vehicles (NGVs) is expected to significantly reduce petroleum and greenhouse gas (GHG) emissions, especially carbon dioxide (CO₂) generated from the transportation sector. On the other hand, considering the lower natural gas price over gasoline price, there is an ongoing debate on increasing the travel demand and higher congestion resulted from NGVs adoption.

Congestion, greenhouse gas emissions, and climate change are three fundamental concerns regarding sustainable development, which are inherently related to each other. Congestion as the result of more travel demand than capacity contributes to greenhouse gas emissions and consequently climate changes (Wang and Chen 2014). Despite the positive impact of higher NGVs use on greenhouse gas emissions and climate change, it is imperative to investigate their negative effect on travel demand and congestion. Increasing the travel demand as a result of higher NGVs use may partially offset benefits of greenhouse gas emissions reduction.
Vehicle Miles Traveled (VMT) is one of the most common measures estimating travel demand in the U.S. and has historically been used to determine the need for new infrastructure. In order to precisely estimate the future components of transportation (such as traffic congestion, GHG emission levels, and required capacity to service the travel demand), accurately forecasting future vehicle miles traveled (VMT) for energy and transportation investment planning is necessary.

While previous studies have investigated the effect of demographic and socioeconomic characteristics, land use, road capacity, and fuel prices on VMT over the U.S. (Bagley and Mokhtarian 2002; Brownstone and Golob 2009; Chatman 2008; Liddle 2009; National Surface Transportation Policy 2007; Noland and Cowart 2000), the effect of natural gas vehicles on VMT has not been fully examined. This study focuses on estimation and forecast of VMT under influence of NGVs. Modeling was conducted using aggregate time series data of Washington State over the period of 1965-2011. Based on the time series data availability of Washington state; VMT was modeled as a function of the number of registered vehicles, employment, and fuel price. Since VMT may go up simply because of the population growth, it is imperative to take this factor into account. Accordingly, the VMT per capita model was developed to exclude the effect of population growth from the model by considering each variable in per capita terms and presents a more plausible model.

In this paper the details of various steps in the time series modeling are presented. The time series analysis was performed using the Box-Jenkins approach to obtain an adequate model for VMT. In order to accurately estimate the models’ coefficients, the
autocorrelation errors and data stationarity were considered. The results demonstrate that increase in use of NGVs will not affect aggregated VMT significantly, even if the share of this type of vehicles is dominant. VMT per capita is, however, relatively more elastic with respect to the rate of NGV adoption. Considering natural gas fuel prices as an attraction and vehicle purchase prices as an obstacle associated with adoption of NGVs over conventional vehicles, sensitivity analysis results demonstrate that VMT and VMT per capita sensitivity with respect to fuel price differential is not considerable, but it could be higher by decreasing purchase differential prices (when NGVs are more affordable).

The presented methodology and estimation results can assist transportation planners and policy-makers in determining future energy and transportation infrastructure investment needs. Moreover, VMT per capita model demonstrates that making policies for VMT reduction may not be effective without considering the population growth.

After a brief literature review, data description presents the trend of different variables during the period of study, which provides us a better understanding of effect of different explanatory variables in these VMT estimation models. Next, in the model estimation section, the process of selecting the most appropriate model is explained, and the identified model was used to forecast future VMT and VMT per capita. After that, using the forecasted models the effect of NGVs adoption on VMT at different combinations of natural gas prices and portions of natural gas vehicles is analyzed. Finally, overall discussion and conclusion is presented at summary and discussion section.
Modeling Methodology

VMT is a continuous variable that changes over time. A time series regression model was developed in order to determine the factors that affect VMT as an aggregated dependent variable. In this study, an econometric model was used to model the VMT demand. The explanatory variables in the model consist of the number of registered vehicles, employment, and gas price. Noted that due to the modeling and forecasting approach of the study, explanatory variables were selected based on their availability in the past and future.

A time series analysis was performed using the Box-Jenkins approach (Box et al. 1994) to obtain an adequate model for VMT. This approach can be divided into three stages: identification, estimation, and diagnosis (Choo et al. 2005). In the identification stage, the response series and a provisional hypothesis about the nature of the model were developed. Tests on autocorrelation of raw series and stationary of data were carried out. After identifying the proper model, the estimation of model parameters was accomplished in the estimation stage using least-squares estimation method. In this study, the SAS software package was used to perform the time series analysis. Finally, in the diagnosis stage the adequacy of the model was evaluated. Significance test for estimated parameters indicates whether some explanatory variables in the model may be unnecessary. Goodness-of-fit statistic provides a benchmark to compare this model to others. Test for white noise residuals indicates whether the residual series contains additional information that might be utilized by a more complex model. There should not be any autocorrelation or other time-dependent trends in the residuals. If the diagnostic
tests identify any problems with the model, another model should be tried, and then the estimation and diagnostic checking stage should be repeated.

Although these three stages take place sequentially, to make the most efficient use of data and improve the estimation accuracy, all parameters from earlier steps are re-estimated simultaneously with parameters relating to the current step. Initially, VMT was modeled as a function of the number of registered vehicles, employment and gas price, which represent socio-demographic, economic, and transportation price factors respectively. Since population alone may significantly influence the VMT growth, the model of VMT on per capita basis was also developed.

This model was estimated based on the aggregate time series data for the state of Washington over the period of 1965-2011. The primarily goal is to estimate the statistical significance and magnitude of the elasticities of VMT with respect to different explanatory variables especially gas price. Elasticity provides a measure of how a change in one variable results in a change in another response variable (i.e., VMT). Empirically, the log-log specification was chosen for the general modeling approach.\(^1\) The log-log form did not change the relative significance of the results compared to a linear formulation. It was useful because it allowed the interpretation of the regression coefficient for each variable as the elasticity of dependant variable with respect to that predictor. In addition, this form provided the absence of heteroskedasticity.

\(^1\) Breusch-Pagan test for heteroskedasticity was performed in SAS for log-log regression results on both VMT and VMT per capita model. Test failed to reject the null hypothesis of constant variance in the residuals (no heteroskedasticity) for both VMT and VMT per capita. On the other hand, similar test for the linear specification showed evidence of heteroskedasticity for VMT model. VMT per capita can be modeled in both log-log and linear form. The log-log form modeling was for easier interpretation of the coefficients.
Data Collected for Model Development

In this study the, aggregate time series data were used to model and predict trips and VMT over time. Due to time and resource constraints, secondary data sources were used. Annual data on VMT for the state of Washington were gathered from Washington State Department of Transportation (WSDOT), Transportation Revenue Forecast Council (2012), and Economic and Revenue Forecast Council (2012). Influences of economic factors, transportation price, and socio-demographic factors during years of 1965-2011 are considered on VMT. The VMT is the dependent variable and the number of registered vehicles, employment, and gas price are explanatory variables. Table 4.1 shows descriptive statistics for the yearly data.

Figure 4.1 shows the growth of VMT during the analysis period. While VMT has been increasing over time, the rate of VMT growth in recent years has been declining. While the growth rate from 1965 to 1998 was around 3.85% per year, it decreased to 0.79% per year from 1998 to 2011. Much of this decrease in rate of VMT growth since 1998 can be attributed to increased gasoline prices, since gasoline prices increased from 1.1 dollars per gallon at 1998 to 3.38 dollars per gallon at 2011. A 1.3% decrease in VMT at 2008 can likely be interpreted as the result of the economic recession.\(^2\) When economic conditions are poor, the unemployment rate rises and the number of recreational activities (shopping, vacation, etc.) usually decreases which has a negative impact on aggregate VMT.

\(^2\)http://stateofworkingamerica.org/great-recession/
Table 4.1 Descriptive statistics of variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observations</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>VMT (billion)</td>
<td>47</td>
<td>38.7</td>
<td>14.27</td>
<td>14.8</td>
<td>57</td>
</tr>
<tr>
<td>Population (million)</td>
<td>47</td>
<td>4.8</td>
<td>1.18</td>
<td>2.96</td>
<td>6.76</td>
</tr>
<tr>
<td>Employment (million)</td>
<td>47</td>
<td>1.9</td>
<td>0.67</td>
<td>0.87</td>
<td>2.96</td>
</tr>
<tr>
<td>Registered vehicle (million)</td>
<td>47</td>
<td>3.8</td>
<td>1.4</td>
<td>1.53</td>
<td>6.16</td>
</tr>
<tr>
<td>Gas price ($/gallon)</td>
<td>47</td>
<td>1.23</td>
<td>0.88</td>
<td>0.19</td>
<td>3.38</td>
</tr>
<tr>
<td>VMT/capita</td>
<td>47</td>
<td>7787</td>
<td>1276</td>
<td>4989</td>
<td>9309</td>
</tr>
</tbody>
</table>

Figure 4.2 shows the trend of gasoline prices in the study period. Two significant price hikes can be observed. The gas price jumped in 1979 more than 2 times due to the second oil crisis. After that, the oil price was stable and did not have any significant change since economic conditions were generally good until 2001. The most critical point for gas prices in the state of Washington, as well as other parts of the U.S., is resulted by the terrorist attack on September 11, 2001. This event dramatically affected gas prices. Since 2001, gas prices have increased from an average of 1.5 dollar per gallon to 3.5 dollars per gallon in 2008. Gasoline prices declined along with the decrease of economic activity that accompanied the onset of the recession, reaching their minimum in late 2008. A few months later, as the economy entered a gradual recovery phase, gasoline prices also trended upward. The number of registered vehicles has been steadily increasing during the study period. This is primarily caused by the increasing population in the state. Figure 4.3 shows that the number of registered vehicles dropped in 2008. The economic recession suppressed the willingness to buy new vehicles and subsequently the number of registered vehicles decreased. This effect continued from 2008 to 2010 by

[^3]: http://www.911memorial.org/
3.6%. The negative effects of the recession have been decreasing and the number of registered vehicles has been increasing since 2010.

Employment is another major index of economic conditions and has a direct effect on the number of trips and VMT. Employment rates indicate the volume of economic activities in society. Figure 4.4 shows the trend of change in employment rates during the period of study. It is clear that the overall trend is positive; however, there are some exceptions in this figure. In particular, employment decreased from 2001 to 2003 by 1.85% as the US entered into the recession following the burst of the dot-com bubble in 2000 and the events of September 11, 2001. These numbers began recovering in 2003 and increased thinly until the beginning of the great recession of 2008. Employment levels continued to fall by 6.1% until 2010 when levels began to increase slightly.

Figure 4.1 Trend of VMT a- whole period study, b- focus of recent years (Billions)
In Figures 4.1 to 4.4, the trend of change in VMT, gas price, the number of registered vehicles and employment are presented. One interesting observation from these figures is that there are periods of time when the VMT generally increases while the gas price also increases and the employment rate decreases. Since 2001, there have been two major drops in employment rates and the prices of gas have increased substantially. Logically, we would expect the VMT to decrease during these time periods. However, no such trend can be observed in Figure 1 except for 2008. Figure 4.5 shows the changes of population and VMT per capita in the study period. The population trend indicates that
the population has been increasing over time. By investigating the trend of VMT per capita, it can be concluded that the largest increases in VMT is due to the population growth. Therefore, we hypothesize that the gas price, employment, and economic activities have more influence on the VMT per capita than VMT.

![Figure 4.4 Trend of Employment](image)

**Figure 4.4 Trend of Employment**
- a- whole period study
- b- focus of recent years

![Figure 4.5 Trend](image)

**Figure 4.5 Trend of**
- a- population
- b- VMT/population

Models Development

In order to control the drastic differences in scale of data without standardizing them, data were transformed into logarithmic form. The validity of the estimated
parameters is based on the assumption of stationary, thus the first step of the proposed approach is to ensure that data are stationary, i.e., their stochastic properties are invariant with respect to time. Since time series data such as those shown in the data description section tend to move upward over time, they needed to be tested for stationary and then transformed, usually by using differences. A time series that would need to be differenced \( P \) times to become a stationary process is categorized as integrated of order \( P \), written as \( I(P) \); hence, a stationary time series is categorized as being integrated of order zero, \( I(0) \). Moreover, serially correlated errors where residuals of a single equation are correlated across two points in time should be eliminated. In order to consider serial correlation in the estimation, the order of auto-regression and moving-average should be determined in the identification stage. For the models of this study, the extended sample autocorrelation function (ESACF) method (Tsay and Tiao 1984) and the smallest canonical (SCAN) correlation method (Tsay and Tiao 1985) were used to tentatively identifying the orders of Integration, Auto-Regressive and Moving-Average.

The identified ARIMA \((p, I, q)\) was specified and led to a set of tentatively useful models. For each estimated model, diagnosis stage was accomplished in different approaches. Augmented Dickey-Fuller unit root test determines whether the order of integration is proper to make row series data stationary or not (Dickey and Fuller 1981). The significance of variables was checked by using the t-test. The Ljung-Box test was used to test for autocorrelation at multiple lags (Ljung and Box 1978). The null hypothesis of Ljung-Box test states that data are independently distributed. That means that the correlations in the population from which the sample is taken are 0, and hence
any observed correlations in data are resulted from the randomness of the sampling process. It should be noted that this test was applied to the residuals of a fitted ARIMA \((p,l,q)\) model to test whether the residuals from the model is white noise or not. In addition, two commonly applied criteria were used as the goodness-of-fit and selection criteria for different estimated time series models (Akaika 1974; Schwarz 1978). The Akaika information criteria (AIC) and Schwarz information criteria (SIC) are given as:

\[
AIC(k) = n\ln(\hat{\sigma}_{ML}^2) + 2k
\]

\[
SIC(k) = n\ln(\hat{\sigma}_{ML}^2) + k\log n
\] (4.1)

where \(n\) denotes the number of effective observations, \(k\) denotes the number of ARIMA parameters to be estimated, \(\hat{\sigma}_{ML}^2 = RSS/n\), and \(RSS\) is the residual sum of squares. The software package SAS was used to estimate the model in this study.

Aggregated VMT Models

Initially, VMT was modeled as a function of three explanatory variables (number of registered vehicles, employment, and gas price) in forms of logarithmic. Since there were correlations between population and employment, the number of registered vehicles was used as the demographic variable instead of population. This model is as below:

\[log_{VMT} = \alpha_0 + \alpha_1 log_{Regveh} + \alpha_2 log_{Empl} + \alpha_3 log_{Gasprice}\] (4.3)

Considering the log-transformed variables, the ESCAF and SCAN tests suggested different order of autoregressive \((p)\), integrated \((I)\), and moving-average \((q)\) as ARIMA \((p,l,q)\) models. The estimation of parameters based on the conditional least
squares (CLS) operation for each of these models was implemented and the results for three VMT models are presented in Table 4.2.

The models suggested by ESCAF and SCAN test are ARIMA (0,1,1), ARIMA (2,1,2) and ARIMA (1,1,2). Since all time series variable was non-stationary even in its logarithmic form, the first order differencing of the logarithmic form series, was used to make them stationary (I(1)). The Ljung-Box test was used for each model to test whether any of a group of autocorrelations is different from zero. Results of the Ljung-Box test at different lags indicated no sufficient evidence to reject the hypothesis that data were independently distributed. Therefore, it can be concluded that the determined order of auto-regressive and moving average to remove autocorrelations were adequate and the residuals of fitted models were with noise. The signs and significance of the explanatory variables are acceptable in all of these models at either 95% or 90% significance level. Because all variables were in logarithmic form, magnitudes of the estimated coefficients can be viewed as direct indicators of the relative impact of the associated explanatory variables on the dependent variable.

The models suggested by ESCAF and SCAN test are ARIMA (0,1,1), ARIMA (2,1,2) and ARIMA (1,1,2). The Ljung-Box test was used for each model to test whether any of a group of autocorrelations was different from zero. Results of the Ljung-Box test at different lags indicated no sufficient evidence to reject the hypothesis that data were independently distributed for ARIMA (0,1,1) and ARIMA (2,1,2). Therefore, it can be concluded that the determined order of auto-regressive and moving average to remove autocorrelations were adequate and the residuals of fitted models were with noise in
ARIMA (0,1,1) and ARIMA (2,1,2) models. The signs and significance of the explanatory variables are acceptable in all of these models at either 0.05 or 0.1 significance level. Because all variables were in logarithmic form, magnitudes of the estimated coefficients can be viewed as direct indicators of the relative impact of the associated explanatory variables on the dependent variable. The number of registered vehicles as a proxy of the demographic situation directly relates to VMT. The increase of vehicles is one of the reasons that lead to more VMT in the state. The coefficients of this variable in the first, second, and third developed models are 0.226, 0.281, and 0.515. The number of registered vehicle variable passes the t-statistic significance test in all three models. The elasticity of VMT with respect to the number of registered vehicles is equal to the corresponding estimated coefficient in each model. The level of employment indicates the level of economic activities of the state. Increasing employment may induce more trips and consequently increase VMT. Hence, the signs of this coefficient in different models are logical. The elasticities of VMT with respect to the employment are 0.267, 0.277, and 0.405 in the first, second, and third models, respectively. All models pass the t-statistic test for this variable. The gas price is expected to have negative impact on VMT since, by increasing the gas price, the willingness to travel falls and VMT should have negative growth. The significance of this variable and its effect on VMT can be confirmed through the t-statistic test in all three models. The elasticities of VMT with respect to the gas price are -0.083, -0.081, and -0.065, respectively, in the first, second, and third models. The adjusted $R^2$ for these estimated models are acceptable and almost
equal. Considering AIC and SIC, the ARIMA \((0,1,1)\) model with lowest AIC and SIC is selected to use as VMT model in rest of the study.

**Aggregated VMT Per Capita Models**

Figure 4.5-a shows that population has been growing in Washington State during the period of study. Increasing population generally leads to more travel demand and subsequently higher VMT. Therefore, to investigate the actual effect of gas price on VMT, it is important to exclude the effect of population on the growth of VMT. The VMT per capita model was developed by using the same set of explanatory variables. However, all values are in per capita terms instead of the whole population. The general form of this model is as below:

\[
log \frac{VMT}{pop} = \beta_0 + \beta_1 log \frac{Regveh}{pop} + \beta_2 log \frac{Empl}{pop} + \beta_3 log \frac{Gasprice}{pop} \tag{4.4}
\]

Table 4.2 Multivariate time series models for vehicle-miles traveled

<table>
<thead>
<tr>
<th>Model ARIMA</th>
<th>Ljung-Box</th>
<th>AIC</th>
<th>SIC</th>
<th>Adj R²</th>
<th>Explanatory Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lag 6</td>
<td>Lag 12</td>
<td>Lag 18</td>
<td>Lag 24</td>
<td></td>
</tr>
<tr>
<td>((0,1,1))</td>
<td>0.423</td>
<td>0.370</td>
<td>0.668</td>
<td>0.637</td>
<td>-231</td>
</tr>
<tr>
<td>((2,1,2))</td>
<td>0.24</td>
<td>0.267</td>
<td>0.601</td>
<td>0.750</td>
<td>-230</td>
</tr>
<tr>
<td>((1,1,2))</td>
<td>0.014</td>
<td>0.015</td>
<td>0.052</td>
<td>0.18</td>
<td>-203</td>
</tr>
</tbody>
</table>

Notes: All dependent and explanatory variables are in the logarithmic form, first order differenced. The number in parentheses states the \(t\)-statistic for each coefficient, the critical value at \(\alpha = 0.05\) and \(\alpha = 0.1\) for first, second and third models are 2.0181 (1.682), 2.0227 (1.685), and 2.021 (1.684), respectively.
Table 4.3 Multivariate time series models for vehicle-miles traveled per capita

<table>
<thead>
<tr>
<th>Model ARIMA</th>
<th>Ljung-Box</th>
<th>AIC</th>
<th>SIC</th>
<th>Adj R²</th>
<th>Explanatory Variable</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>Lag 6</td>
<td></td>
<td></td>
<td></td>
<td>Constant</td>
</tr>
<tr>
<td>(0,1,1)</td>
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<td>0.011 (2.25)</td>
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<tr>
<td></td>
<td>0.42</td>
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<td></td>
<td></td>
<td>Registered Vehicles</td>
</tr>
<tr>
<td></td>
<td>0.73</td>
<td></td>
<td></td>
<td></td>
<td>0.25 (2.85)</td>
</tr>
<tr>
<td></td>
<td>0.65</td>
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<td>Employment</td>
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<td>0.22 (1.46)</td>
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<td></td>
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<td>Gas price</td>
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<tr>
<td>(1,1,2)</td>
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<td>-222</td>
<td>0.989</td>
<td>0.021 (2.21)</td>
</tr>
<tr>
<td></td>
<td>0.51</td>
<td></td>
<td></td>
<td></td>
<td>0.295 (3.23)</td>
</tr>
<tr>
<td></td>
<td>0.88</td>
<td></td>
<td></td>
<td></td>
<td>0.174 (1.33)</td>
</tr>
<tr>
<td></td>
<td>0.85</td>
<td></td>
<td></td>
<td></td>
<td>-0.098 (-5)</td>
</tr>
<tr>
<td>(2,1,2)</td>
<td>0.51</td>
<td></td>
<td>-214</td>
<td>0.989</td>
<td>0.014 (1.68)</td>
</tr>
<tr>
<td></td>
<td>0.40</td>
<td></td>
<td></td>
<td></td>
<td>0.276 (3.04)</td>
</tr>
<tr>
<td></td>
<td>0.77</td>
<td></td>
<td></td>
<td></td>
<td>0.163 (1.14)</td>
</tr>
<tr>
<td></td>
<td>0.74</td>
<td></td>
<td></td>
<td></td>
<td>-0.99 (-4.8)</td>
</tr>
</tbody>
</table>

Notes: All dependent and explanatory variables are in the logarithmic form, first order differenced. The number in parentheses states the t-statistic for each coefficient, the critical value at \( \alpha = 0.05 \) and \( \alpha = 0.1 \) for first, second, and third models are 2.0181 (1.682), 2.0227 (1.685), and 2.0227 (1.685), respectively.

Figure 4.5-b shows the trend of VMT per capita. The figure actually makes more sense because higher gas price is expected to discourage travel demand and result in fewer VMT. Therefore, it is concluded that the most part of the VMT growth in recent years can be attributed to the population increase. Table 4.3 presents three models suggested for the VMT per capita model using ESCAF and SCAN tests. Based on the result of the Ljung-Box test, all models pass the white noise check, which implies that the effect of the autocorrelation between residuals at different lag times was removed. Coefficients associated with different variables are significant based on t-statistic test, and have proper signs as were expected. While the adjusted \( R^2 \) is the equal in these three models, AIC and SIC suggest the \( ARIMA (0,1,1) \) as the best fitted model to be used in the rest of this study as VMT per capita model.

Data and Model Analysis

In previous sections, VMT and VMT per capita models were fitted based on Washington State data. The selected models for VMT and VMT per capita models are
ARIMA (0,1,1). The main goal of this section is to analyze the effect of natural gas vehicles on future trips based on these fitted models. The forecasting and sensitivity analysis were accomplished for both the aggregated VMT and VMT per capita. The analysis is based on the portion of natural gas vehicles, which was estimated for the Washington State based on the methodology proposed by Barnes et al. (2014).

Natural gas vehicles percentage

Considering only economic factors, rational costumers would choose to purchase natural gas vehicles (NGV) if they find cost advantages in switching to NGVs from conventional fuel vehicles (Barnes et al. 2014). The price of the vehicle, the cost of fuel, expected vehicle miles traveled (VMT), fuel efficiency (i.e., MPG), and the expected vehicle useful life are primary factors that costumers consider. Let $V_{g0}^*$ and $V_{co}^*$ be the differences between the purchase price and the discounted salvage value after the end of the vehicle’s useful life of conventional gasoline vehicles and NGVs, respectively. $f_g$ and $f_c$ are defined as the fuel expense per period for the gasoline vehicle and NGV respectively, and $r$ is the customer discount rate. When the gasoline vehicle is more expensive, consumers will choose to purchase a NGV:

$$\Delta TC = (V_{g0}^* - V_{c0}^*) + \sum_{t=0}^{T} (1 + r)^{-t} (f_g - f_c) > 0$$ (4.5)

Using the Washington State data from the 2009 NHTS, the proportion of the fleet that falls into this specific (VMT, MPG) combination was computed. Based on the joint distribution of household VMT and MPG in the 2009 NHTS, assumptions about the purchase price differential and fuel price differential, the proportion of the fleet that
would be financially advantageous if NGVs are chosen can be calculated. These predicted adoption rates is presented in Table 4.4.

Table 4.4 Proportion of NGV in Washington State

<table>
<thead>
<tr>
<th>Fuel price differential</th>
<th>Purchase price differential</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1.20</td>
<td>12.9% 2.2% 0.8% 0.3% 0%</td>
</tr>
<tr>
<td>$1.30</td>
<td>19.9% 6.2% 1.3% 0.5% 0%</td>
</tr>
<tr>
<td>$1.40</td>
<td>25.9% 8.9% 1.6% 0.8% 0.3%</td>
</tr>
<tr>
<td>$1.50</td>
<td>28.6% 12.1% 2.2% 0.8% 0.3%</td>
</tr>
<tr>
<td>$1.60</td>
<td>31.0% 12.9% 4.6% 1.3% 0.5%</td>
</tr>
<tr>
<td>$1.70</td>
<td>35.3% 17.3% 7.3% 1.6% 0.8%</td>
</tr>
<tr>
<td>$1.80</td>
<td>38.3% 23.5% 10.2% 2.2% 1.1%</td>
</tr>
<tr>
<td>$1.90</td>
<td>42.6% 25.9% 12.1% 4.3% 1.6%</td>
</tr>
<tr>
<td>$2.00</td>
<td>46.1% 28.6% 12.9% 6.5% 1.6%</td>
</tr>
<tr>
<td>$2.10</td>
<td>50.4% 30.5% 16.4% 8.9% 2.2%</td>
</tr>
<tr>
<td>$2.20</td>
<td>52.0% 33.4% 19.9% 10.8% 4.3%</td>
</tr>
<tr>
<td>$2.30</td>
<td>55.8% 37.5% 23.5% 12.1% 6.5%</td>
</tr>
<tr>
<td>$2.40</td>
<td>57.4% 38.3% 26.4% 12.9% 7.8%</td>
</tr>
<tr>
<td>$2.50</td>
<td>59.3% 41.8% 28.6% 16.2% 10.2%</td>
</tr>
</tbody>
</table>

Forecasting

In order to forecast the VMT and VMT per capita, the forecasted values of explanatory variables were taken from the WSDOT Economic Analysis, the Washington State Transportation Revenue Forecast Council (2012), and the Washington State Economic and Revenue Forecast Council (2012). While natural gas is cheaper than gasoline, the question then arises as to how much VMT will be induced by higher use of NGVs. The effect of natural gas vehicles on future VMT were investigated using the average fuel price instead of fuel price variable. Average fuel price is defined as weighted average of fuel price for natural gas vehicles and gasoline vehicles with respect to their proportion in the fleet. Average fuel price for forecasting is defined as:
Average fuel price = \( \sum_i p_i * k_i \)  

(4.6)

where \( p_i \) is the forecasted unit price of fuel type \( i \) and \( k_i \) is the forecasted proportion of vehicles type \( i \) in the fleet. The estimated NGV adoption rate was used to calculate average fuel price for forecasting. The estimates for the adoption rates above present a large range of plausible parameter values. The sensitivity of our forecasts to this parameter has been tested. Nine scenarios of NGV’s proportion were presented based on combinations of fuel differential price of $1.50, $2.00, and $2.50 per gallon and purchase price differentials of $3000, $6000, and $9000. These scenarios are presented in Table 4.5.

Table 4.6 presents the forecasted VMT in these different scenarios. Scenario 1 is the baseline scenario, as there will be no NGV in the fleet, and other scenarios imply different proportion of NGV. The baseline scenario results indicate that VMT will continue to grow even without NGV adoption. Other scenarios, which are influenced by NGVs, all forecast greater VMT. As the portion of NGVs in the fleet increases, there is a corresponding induced increase in VMT.

Table 4.5 Different Scenarios to forecast VMT

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Fuel price differential</th>
<th>Purchase price differential</th>
<th>NGV’s portion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.5$</td>
<td>9000$</td>
<td>0%</td>
</tr>
<tr>
<td>2</td>
<td>2$</td>
<td>9000$</td>
<td>0.5%</td>
</tr>
<tr>
<td>3</td>
<td>2.5$</td>
<td>9000$</td>
<td>1.6%</td>
</tr>
<tr>
<td>4</td>
<td>1.5$</td>
<td>6000$</td>
<td>0.8%</td>
</tr>
<tr>
<td>5</td>
<td>2$</td>
<td>6000$</td>
<td>6.5%</td>
</tr>
<tr>
<td>6</td>
<td>2.5$</td>
<td>6000$</td>
<td>16.2%</td>
</tr>
<tr>
<td>7</td>
<td>1.5$</td>
<td>3000$</td>
<td>28.6%</td>
</tr>
<tr>
<td>8</td>
<td>2$</td>
<td>3000$</td>
<td>46.1%</td>
</tr>
<tr>
<td>9</td>
<td>2.5$</td>
<td>3000$</td>
<td>59.3%</td>
</tr>
</tbody>
</table>
Table 4.6 Forecasted change from 2012 VMT (Billion) due to NGV Adoption

<table>
<thead>
<tr>
<th>Year</th>
<th>Scenario 1 (Baseline)</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
<th>Scenario 4</th>
<th>Scenario 5</th>
<th>Scenario 6</th>
<th>Scenario 7</th>
<th>Scenario 8</th>
<th>Scenario 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>1.80</td>
<td>(-0.01)</td>
<td>(+0.05)</td>
<td>(+0.02)</td>
<td>(+0.18)</td>
<td>(+0.57)</td>
<td>(+0.61)</td>
<td>(+1.43)</td>
<td>(+2.57)</td>
</tr>
<tr>
<td>2014</td>
<td>3.55</td>
<td>(-0.01)</td>
<td>(+0.05)</td>
<td>(+0.02)</td>
<td>(+0.18)</td>
<td>(+0.58)</td>
<td>(+0.62)</td>
<td>(+1.44)</td>
<td>(+2.59)</td>
</tr>
<tr>
<td>2015</td>
<td>5.54</td>
<td>(-0.01)</td>
<td>(+0.06)</td>
<td>(+0.02)</td>
<td>(+0.19)</td>
<td>(+0.61)</td>
<td>(+0.65)</td>
<td>(+1.53)</td>
<td>(+2.76)</td>
</tr>
<tr>
<td>2016</td>
<td>7.32</td>
<td>(-0.01)</td>
<td>(+0.06)</td>
<td>(+0.02)</td>
<td>(+0.19)</td>
<td>(+0.62)</td>
<td>(+0.66)</td>
<td>(+1.54)</td>
<td>(+2.78)</td>
</tr>
<tr>
<td>2017</td>
<td>8.92</td>
<td>(-0.01)</td>
<td>(+0.06)</td>
<td>(+0.02)</td>
<td>(+0.19)</td>
<td>(+0.60)</td>
<td>(+0.64)</td>
<td>(+1.49)</td>
<td>(+2.67)</td>
</tr>
<tr>
<td>2018</td>
<td>10.96</td>
<td>(-0.02)</td>
<td>(+0.06)</td>
<td>(+0.02)</td>
<td>(+0.20)</td>
<td>(+0.65)</td>
<td>(+0.69)</td>
<td>(+1.62)</td>
<td>(+2.92)</td>
</tr>
<tr>
<td>2019</td>
<td>13.09</td>
<td>(-0.02)</td>
<td>(+0.07)</td>
<td>(+0.02)</td>
<td>(+0.22)</td>
<td>(+0.72)</td>
<td>(+0.77)</td>
<td>(+1.81)</td>
<td>(+3.28)</td>
</tr>
<tr>
<td>2020</td>
<td>14.77</td>
<td>(-0.02)</td>
<td>(+0.07)</td>
<td>(+0.02)</td>
<td>(+0.22)</td>
<td>(+0.72)</td>
<td>(+0.77)</td>
<td>(+1.81)</td>
<td>(+3.27)</td>
</tr>
<tr>
<td>2021</td>
<td>16.64</td>
<td>(-0.02)</td>
<td>(+0.07)</td>
<td>(+0.02)</td>
<td>(+0.23)</td>
<td>(+0.74)</td>
<td>(+0.79)</td>
<td>(+1.86)</td>
<td>(+3.36)</td>
</tr>
<tr>
<td>2022</td>
<td>18.47</td>
<td>(-0.02)</td>
<td>(+0.07)</td>
<td>(+0.02)</td>
<td>(+0.23)</td>
<td>(+0.76)</td>
<td>(+0.80)</td>
<td>(+1.89)</td>
<td>(+3.42)</td>
</tr>
<tr>
<td>2023</td>
<td>20.45</td>
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<td>(+0.07)</td>
<td>(+0.02)</td>
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<td>(+0.78)</td>
<td>(+0.83)</td>
<td>(+1.96)</td>
<td>(+3.55)</td>
</tr>
<tr>
<td>2024</td>
<td>22.28</td>
<td>(-0.02)</td>
<td>(+0.07)</td>
<td>(+0.02)</td>
<td>(+0.24)</td>
<td>(+0.78)</td>
<td>(+0.83)</td>
<td>(+1.95)</td>
<td>(+3.52)</td>
</tr>
<tr>
<td>2025</td>
<td>24.42</td>
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<td>(+0.08)</td>
<td>(+0.02)</td>
<td>(+0.25)</td>
<td>(+0.81)</td>
<td>(+0.87)</td>
<td>(+2.03)</td>
<td>(+3.68)</td>
</tr>
<tr>
<td>2026</td>
<td>26.28</td>
<td>(-0.02)</td>
<td>(+0.07)</td>
<td>(+0.02)</td>
<td>(+0.25)</td>
<td>(+0.80)</td>
<td>(+0.85)</td>
<td>(+1.99)</td>
<td>(+3.58)</td>
</tr>
<tr>
<td>2027</td>
<td>28.21</td>
<td>(-0.02)</td>
<td>(+0.07)</td>
<td>(+0.02)</td>
<td>(+0.24)</td>
<td>(+0.79)</td>
<td>(+0.84)</td>
<td>(+1.96)</td>
<td>(+3.50)</td>
</tr>
<tr>
<td>2028</td>
<td>30.18</td>
<td>(-0.02)</td>
<td>(+0.07)</td>
<td>(+0.02)</td>
<td>(+0.24)</td>
<td>(+0.78)</td>
<td>(+0.83)</td>
<td>(+1.92)</td>
<td>(+3.42)</td>
</tr>
<tr>
<td>2029</td>
<td>32.30</td>
<td>(-0.02)</td>
<td>(+0.07)</td>
<td>(+0.02)</td>
<td>(+0.24)</td>
<td>(+0.78)</td>
<td>(+0.83)</td>
<td>(+1.92)</td>
<td>(+3.42)</td>
</tr>
<tr>
<td>2030</td>
<td>34.81</td>
<td>(-0.02)</td>
<td>(+0.08)</td>
<td>(+0.02)</td>
<td>(+0.25)</td>
<td>(+0.82)</td>
<td>(+0.87)</td>
<td>(+2.03)</td>
<td>(+3.62)</td>
</tr>
<tr>
<td>2031</td>
<td>37.00</td>
<td>(-0.02)</td>
<td>(+0.08)</td>
<td>(+0.02)</td>
<td>(+0.25)</td>
<td>(+0.82)</td>
<td>(+0.87)</td>
<td>(+2.02)</td>
<td>(+3.59)</td>
</tr>
</tbody>
</table>

The low fuel price elasticity of VMT states that introducing natural gas vehicles will not have much effect on future VMT. Scenario 9 is potentially an extreme case, where nearly 60% of vehicles run on natural gas. This portion of natural gas vehicles induces an extra 3.62 billion VMT in 2031 over the 37 billion VMT without natural gas vehicles in baseline scenario. Increasing the share of natural gas vehicles to 60% will only induce less than 9.9% additional VMT. Even this rather modest increase is based on an assumption of extremely favorable circumstances for natural gas vehicles: a $3000 purchase price differential and $2.50 fuel price differential. This scenario would require a concentrated effort from car manufactures to substantially lower prices for natural gas vehicles as well as a dramatic divergence between the price of gasoline and natural gas.
Therefore, it is unlikely that VMT projection will be radically altered by the introduction of a large proportion of NGV.

The results of forecasting VMT per capita under influence of NGV in different scenarios are presented in Table 4.7. It is demonstrated that under a no-change scenario (scenario 1), there will be 2155 more VMT per capita at 2031 over 2012 levels. The estimated induced VMT per person by NGVs at 2031 is around 19% in scenario 9 (utmost NGV portion).

Table 4.7 Forecasted change in Per Capita VMT from 2012 Levels due to NGV Adoption

<table>
<thead>
<tr>
<th>Year</th>
<th>Scenario 1 (Baseline)</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
<th>Scenario 4</th>
<th>Scenario 5</th>
<th>Scenario 6</th>
<th>Scenario 7</th>
<th>Scenario 8</th>
<th>Scenario 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>150.54</td>
<td>(+2.23)</td>
<td>(-8.85)</td>
<td>(+2.67)</td>
<td>(-29.47)</td>
<td>(+95.88)</td>
<td>(-101.96)</td>
<td>(+238.90)</td>
<td>(+431.16)</td>
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<tr>
<td>2014</td>
<td>286.19</td>
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<td>(+8.94)</td>
<td>(+2.67)</td>
<td>(+29.46)</td>
<td>(+95.76)</td>
<td>(-101.83)</td>
<td>(+238.21)</td>
<td>(+428.82)</td>
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<td>(-9.33)</td>
<td>(+2.79)</td>
<td>(+30.73)</td>
<td>(+99.99)</td>
<td>(-106.34)</td>
<td>(+249.35)</td>
<td>(+450.56)</td>
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<tr>
<td>2016</td>
<td>571.91</td>
<td>(+2.32)</td>
<td>(-9.31)</td>
<td>(+2.78)</td>
<td>(+30.60)</td>
<td>(+99.70)</td>
<td>(-106.02)</td>
<td>(+248.20)</td>
<td>(+447.35)</td>
</tr>
<tr>
<td>2017</td>
<td>661.85</td>
<td>(+2.22)</td>
<td>(+8.94)</td>
<td>(+2.67)</td>
<td>(+29.42)</td>
<td>(+95.44)</td>
<td>(-101.47)</td>
<td>(+236.38)</td>
<td>(+422.76)</td>
</tr>
<tr>
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<td>(+2.37)</td>
<td>(-9.53)</td>
<td>(+2.85)</td>
<td>(+31.38)</td>
<td>(+102.04)</td>
<td>(-108.50)</td>
<td>(+253.93)</td>
<td>(+457.41)</td>
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<tr>
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<td>(+3.09)</td>
<td>(+34.11)</td>
<td>(+111.24)</td>
<td>(-118.33)</td>
<td>(+278.81)</td>
<td>(+507.72)</td>
</tr>
<tr>
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<td>(+3.06)</td>
<td>(+33.75)</td>
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<td>1193.04</td>
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<td>(+10.38)</td>
<td>(+3.10)</td>
<td>(+34.21)</td>
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<td>(+509.17)</td>
</tr>
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<td>(+10.80)</td>
<td>(+3.23)</td>
<td>(+35.60)</td>
<td>(+115.97)</td>
<td>(-123.34)</td>
<td>(+289.80)</td>
<td>(+525.34)</td>
</tr>
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<td>1750.30</td>
<td>(+2.62)</td>
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<td>(+3.14)</td>
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<td>(+504.68)</td>
</tr>
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<td>(+2.96)</td>
<td>(+32.55)</td>
<td>(+105.44)</td>
<td>(-112.09)</td>
<td>(+260.13)</td>
<td>(+462.55)</td>
</tr>
<tr>
<td>2030</td>
<td>2219.78</td>
<td>(+2.56)</td>
<td>(+10.29)</td>
<td>(+3.07)</td>
<td>(+33.86)</td>
<td>(+109.79)</td>
<td>(-116.71)</td>
<td>(+271.46)</td>
<td>(+484.29)</td>
</tr>
<tr>
<td>2031</td>
<td>2333.96</td>
<td>(+2.53)</td>
<td>(+10.15)</td>
<td>(+3.03)</td>
<td>(+33.41)</td>
<td>(+108.21)</td>
<td>(-115.03)</td>
<td>(+266.96)</td>
<td>(+484.29)</td>
</tr>
</tbody>
</table>

Comparing VMT and VMT per capita projection in scenario 9, it is concluded that NGV adoption rates will have a greater effect on VMT per capita, due to the higher sensitivity of VMT per capita with respect to fuel prices. Considering scenario 1, at 2031 the VMT will be increased by 64%, while VMT per capita will have 26% increment. This
demonstrates that the significant portion of VMT increment is due to the population growth. Figure 4.6 presents the forecasted value of number of registered vehicles per capita, employment rate per capita, and gasoline price trend. While VMT per capita has been decreasing over recent years, the considerable reduction in gasoline price growth rate leads to higher VMT per capita in future. Besides, the tiny increment in growth rate of number of registered vehicles per capita has positive effect on VMT per capita.

Sensitivity Analysis

VMT forecasts are sensitive to a number of factors. Fuel price is one of the main explanatory factors in the variation of the VMT models. Fuel price was considered as a weighted average of prices using the predicted adoption rates. The NGV adoption rate was determined based on the purchase price differential and fuel price differential between gasoline vehicles and NGVs. Therefore, these two variables are the main source of differentiation in VMT and VMT per capita forecasts. Figures 4.7 and 4.8 depict the sensitivity of VMT and VMT per capita to with respect to purchase price differential and fuel price differential. Higher fuel price differential and lower purchase price differential, which are the attractiveness of NGVs, increase the VMT and VMT per capita.

From these figures, it is clear that VMT and VMT per capita are more sensitive to fuel price differential when the purchase price differential is small. The main obstacle associated with adoption of NGVs is the large upfront purchase price differential.
Figure 4.6 Forecasted value of a-number of registered vehicles per capita, b-employment rate per capita, c-gasoline price

Figure 4.7 Sensitivity of total VMT by differential of fuel cost and upfront purchase price at 2031
Summary and Discussion

This study helps WSDOT assess the impacts of changes in fuel price on travel demand, particularly how NGV adoption with lower fuel price affects VMT. The VMT as a measure of travel demand was modeled by using time series data. The data was taken from WSDOT from 1965-2011. VMT was regressed by an ARIMA \((0,1,1)\) on the number of registered vehicles, employment, and gas price. Based upon this model, estimated elasticity of VMT with respect to number of registered vehicles, employment and gas price are 0.226, 0.267, and -0.083, respectively. In addition to the VMT model, another model was adapted to exclude population effects. An ARIMA \((0,1,1)\) for VMT per capita model was fitted using per capita versions of the same explanatory variables. The estimated coefficient of this model for number of registered vehicles per capita,
employment per capita and gas price are 0.286, 0.220, and -0.096, respectively. These estimates imply that VMT per capita is more sensitive to the fuel price than VMT.

Moreover, VMT was forecasted in multiple scenarios by assuming the natural gas price and the associated adoption rate. The results specified that due to the low fuel price elasticity of aggregated automobile use (both VMT and VMT per capita) induced travel by NGVs will not considerable. The forecasted VMT at 2031 will be increased by 37 billion without NGV in fleet, while increasing the NGV to 60% of vehicle fleet will induce 9.9% VMT at 2031. VMT per capita without NGV at 2031 will be increased by 2155 and increasing NGV to 60% of vehicle fleet will induce 19%.

Regarding different environmental and fuel dependency aspects, comprising 60% vehicle fleet by NGVs is idealistic. Based on the methodology used by Barnes et al. (2014), decreasing differential purchase price and raising differential fuel price are important in encouraging commuters to adopt natural gas. Considering result of sensitivity analysis, in order to have considerable NGV share, much efforts from car manufactures are needed to substantially decrease the natural gas vehicles price. Converging price of natural gas and conventional vehicles, a dramatic divergence between the price of gasoline and natural gas also is imperative.

While conducting policy to improve fuel efficiency increases the VMT and gasoline consumption through rebound effect (see chapter 5), policies regarding increase the use of NGVs would have no concerns about inducement of considerable VMT, as well as gasoline consumption. Considering results of this study, policy implication to
increase the attraction of NGVs is beneficial. Decreasing NGVs purchase price and natural gas fuel price are two imperative actions to increase the use of NGVs.

The results of models and data analysis demonstrated that considerable amount of VMT growth is due to population. Gasoline price increment is another VMT controlling policies. It has negative effect on VMT through the coefficient of fuel price on VMT model. On the other hand, it increases the use of NGVs, which slightly induces VMT. However, due to the negligible share of NGVs the consequence of these effects is decreasing on VMT. The fuel price coefficient in VMT per capita model, which is population-controlled model, is more than VMT model. It demonstrates the increasing the gasoline price to decrease the VMT is more effective when the population has no increment.

References


CHAPTER 5

FUTURE OF FUEL TAX REVENUE AND GHG EMISSIONS BY IMPROVING FUEL EFFICIENCY

Abstract

However fuel economy improvement has been proven to be one of the most effective policies in controlling oil demand and GHG emissions in the transportation sector, it results in decrease of fuel tax revenue, which is the main funding source for building and maintaining transportation infrastructures in the USA. This may be challenging for government due to substantial increase in transportation construction and maintenance costs. On the other hand, improvement of fuel efficiency reduces the marginal and average cost of travel, thereby encouraging drivers to drive more, which in turn increases the gasoline consumption. The objective of this study is to estimate the potential loss of fuel tax revenue and GHG emissions, which are dependents of fuel consumption, resulted from the fuel efficiency improvement. Accordingly, fuel consumption was modeled as a system of equations consisting of vehicle miles traveled (VMT) and fuel efficiency (MPG) as two explanatory variables. The model was estimated by 3 Stage Least Square (3SLS) method, using annual time series data for Washington State over the time period of 1976-2011. According to the results, Washington State will have 106 million dollars loss in revenue and 8.7% reduction in CO$_2$ in 2031.

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Introduction

Transportation is one of the major energy consuming sectors in the U.S\(^5\) (Davis et al. 2014). The continued growth in fuel consumption not only increases dependency on foreign oil but also causes environmental issues due to the emissions of greenhouse gas (GHG). Improvement in automobile fuel economy has been proven to be one of the most effective policies in controlling oil demand and GHG emissions in transportation sector around the world (An and Sauer 2004). Conversely, increase of fuel efficiency also raises some concerns about potential negative effects on fuel tax revenue.

There are three principal road tax revenue options: user charges based on fuel consumption, user charges based on distance traveled, and user charges based on congestion (Huang et al. 2010). Over the past sixty years, the fuel tax has been the primary funding source for building and maintaining highway infrastructure in the U.S. Similar to other parts of the country, Washington State is concerned about rising construction and maintenance costs and declining fuel tax revenue. The increase of fuel-efficient vehicles results in less fuel consumption per mile traveled which means fewer tax dollars for the same amount of road use. Despite the negative impact on fuel tax revenue, this trend is favorable for the environment and energy security. Due to importance of economical and environmental issues on society, understanding various potential outcomes of fuel efficiency improvement is vital for governments. Analysis of the effects of fuel efficiency improvement on revenue and emissions is not possible without considering the behavior of fuel consumption.

\(^5\) Transportation consumes 28% of total energy use and 67% of total petroleum use.
Besides the effect of fuel efficiency on fuel consumption reduction, higher fuel efficiency reduces the cost of travel, thereby encouraging drivers to drive more, which in turn increases the gasoline consumption (Small and Van Dender 2007). This increment in gasoline consumption, which is defined as rebound effect, offsets some of the energy-saving benefit of fuel efficiency improvement. Therefore, in order to estimate the future fuel tax revenue and GHG emissions, the rebound effect should be considered.

Some empirical studies on fuel consumption elasticity and rebound effect use aggregate time-series data and some rely on pooled cross sectional time-series data. Greene (1992) developed a linear single VMT model to estimate the fuel efficiency elasticity of fuel consumption and rebound effect. Using the aggregate annual U.S. data for 1957 to 1989, he estimated that both short and long run rebound effects are between 5% and 15%, with a best estimate of 12.7%. The results were based on the model developed using lagged values of VMT to release autocorrelation. Jones (1993) used Greene’s data with additional observations of 1990. The model structures adopted were single static and dynamic of linear and log-linear functional forms. The long-run rebound effect was found to be twice as large as the short-run estimation (roughly 30% vs. 13%). Schimek (1996) used the U.S. aggregate data from 1950 to 1994, and adopted a recursive structure model in double-log form. It is showed that the single-equation results are inevitably subject to the endogeneity bias. This occurs when explanatory variables in a single equation are actually endogenous to the system of interest rather than exogenous. The short- and long-run rebound effects were estimated to be 5-7% and 21-29%, respectively.
Small and Van Dender (2007) modeled the fuel efficiency as an endogenous variable. Their investigation on rebound effect demonstrated 4.5% and 22% fuel saving offset in short run and in long run, respectively. In another study, Mayo and Mathis (1988) estimated the effect of fuel efficiency and fuel price on fuel consumption. Their model was a system of equations with fuel efficiency as the endogenous variable. They found rebound effects of 22% and 26% in short run and in long run, respectively.

By reviewing different studies, it is concluded that the model structure and estimation techniques are critical in analysis of the rebound effect as well as fuel consumption. Based on literature reviews done by De Jong and Gunn (2001), Graham and Glaister (2002), and Goodwin et al. (2004), short-run rebound effects are reported to be 10-20%. Therefore, 14% short-run rebound effect estimated in this study complies with results from previous studies. In this study the system of equations model was estimated using 3SLS method to achieve unbiased and consistent results. Furthermore, the autoregressive model was used to release the effect of autocorrelation of each model residuals. The order of auto-regression was obtained by conducting tests on each single equation.

The goal of this study is to estimate the potential loss of fuel tax revenue and GHG emissions resulted from the increasing fuel efficiency. Models of vehicle miles traveled (VMT) and fuel efficiency (MPG) were developed using Washington State annual time series data from 1976 to 2011. Fuel tax revenue and GHG emissions were analyzed based upon the estimated results.
The data and proposed variables used for the model estimation are shown in following section. The methodology of this study is described afterward. After that, estimation methods and results are presented, which is followed by the revenue and GHG emission analysis. Finally, the primary findings of this paper will be discussed in the conclusion section.

Data

The aggregate time series data was used to estimate parameters of this study model. Due to the time and resource constraints, secondary data sources were used. Annual data for the State of Washington from 1976 to 2011 were gathered from the Washington State Department of Transportation (WSDOT), the Transportation Revenue Forecast Council (2012), and Economic and Revenue Forecast Council (2012). Factors such as economic factors, transportation costs, and socio-demographic factors were considered in this study. Variables that can be extracted from the dataset include: the quantity of gasoline consumed, the price of gasoline, vehicle miles traveled, number of registered vehicles, and employment. Table 5.1 presents the descriptive statistics of these variables.

Figure 5.1 shows the positive growth of VMT during the analysis period. However, the VMT has been increasing over years, the rate of VMT growth recent years has been declining. While the growth rate from 1976 to 1998 was around 3.4% per year, it was decreased to 0.79% per year from 1998 to 2011. Much of the decrements in rate of VMT growth since 1998 can be attributed to increased gasoline prices, since gasoline
price was raised from 1.1 dollars per gallon at 1998 to 3.38 dollars per gallon at 2011. Figure 5.2 shows changes in gasoline prices over the same timeframe. The number of registered vehicles has steadily increased during the period of study. Figure 5.3 shows that the number of registered vehicles dropped from 6.16 million in 2008 to 5.94 million in 2010 at the time of the economic downturn. However, since 2010 the number of registered vehicles began to increase. Employment is indicative of the volume of economic activity and has a direct effect on VMT. Therefore, when employment is high, VMT is generally high to accommodate this activity. Figure 5.4 shows employment during the period of study. It is clear that the overall trend is positive as would be expected with a growing population. However, there is also notable variation in this figure. In particular, employment decreased from 2001 (2.71 million) to 2003 (2.65 million) as the US entered into the recession following the burst of the dot-com bubble in 2000 and the events of September 11, 2001. These numbers begins recovering 2003 and increased thinly until the beginning of the great recession of 2008 (2.96 million). Employment levels continued to fall until 2010 (2.78 million) when levels begin to increase slightly. Figure 5.5 shows the trend of MPG during the study period. The MPG has been increasing over time. It can be primarily explained by the technology development in the auto industry. In order to combat increasing fuel consumption, USDOT established policies for auto manufacturers to improve fuel-efficiency in vehicles.

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6 http://stateofworkingamerica.org/great-recession/
7 http://www.911memorial.org/
Table 5.1 Descriptive statistics of variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of observation</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>VMT (billion)</td>
<td>36</td>
<td>44.5</td>
<td>10.8</td>
<td>24.7</td>
<td>57</td>
</tr>
<tr>
<td>Gas consumption (billion)</td>
<td>36</td>
<td>2.34</td>
<td>0.35</td>
<td>1.77</td>
<td>2.76</td>
</tr>
<tr>
<td>Employment (million)</td>
<td>36</td>
<td>2.2</td>
<td>0.52</td>
<td>1.24</td>
<td>2.96</td>
</tr>
<tr>
<td>Registered vehicle (million)</td>
<td>36</td>
<td>4.4</td>
<td>1.12</td>
<td>2.48</td>
<td>6.16</td>
</tr>
<tr>
<td>Gas price ($/gallon)</td>
<td>36</td>
<td>1.53</td>
<td>0.78</td>
<td>0.41</td>
<td>3.38</td>
</tr>
<tr>
<td>MPG = VMT/Gas consumption (mile / gallon)</td>
<td>36</td>
<td>18.75</td>
<td>2.16</td>
<td>13.93</td>
<td>21.2</td>
</tr>
<tr>
<td>Travel cost = Gas price/MPG ($/mile)</td>
<td>36</td>
<td>0.08</td>
<td>0.034</td>
<td>0.029</td>
<td>0.16</td>
</tr>
</tbody>
</table>

Figure 5.1 Trend of VMT data 1976-2011
Figure 5.2 Trend of gas price data 1976-2011

Figure 5.3 Trend of number of registered vehicles data 1976-2011,
Figure 5.4 Trend of employment data 1976-2011

Figure 5.5 Trend of MPG data 1976-2011
Methodology

There is an ongoing debate on how the improving fuel efficiency reduces the fuel consumption. Fuel efficiency is defined as total miles traveled per gallon gasoline consumption. Its variations could be resulted from 1- manufacturers’ adjustment of relative price of different vehicle make and models, 2- consumers’ adjustments via purchase of various vehicle make and models, 3- consumers’ decisions about vehicle repairing and services, and 4- driving habits (Small and Van Dender 2007).

The gasoline demand is a derived demand that is completely related to demand for travel services, and it contains certain behavioral and technological components. These components are related to how much individuals travel and the size and potential fuel efficiency of the vehicle fleet (Blair et al. 1984). Gasoline consumption ($g$) and fuel cost per mile ($c$) can be defined as follows:

\[ g = \frac{m}{e} \quad (5.1) \]

and

\[ c = \frac{p}{e} \quad (5.2) \]

where $m$ is the vehicle miles traveled (VMT), $e$ is the realized fuel efficiency (MPG) in mile per gallon and $p$ is fuel price per gallon. In order to derive the fuel consumption, VMT and MPG equations should be estimated.

Fuel cost ($c$) as a function of fuel price ($p$) and fuel efficiency ($e$) is one effective factor in the VMT ($m$) equation. Increasing fuel price discourages users from conducting more trips, which results in fewer VMT. On the other hand, improvement in fuel
efficiency may surpass the impact of fuel price leading to higher VMT. Therefore, both the fuel price and fuel efficiency were considered as exogenous variables in the VMT model. In addition to the above-mentioned factors, the number of registered vehicles (Regveh variable) and employment (Emp variable) were used as exogenous variables to represent demographic and economic conditions. In some other studies, population and income were used instead of number of registered vehicles and employment (Mayo and Mathis 1988). For the purpose of this study, the one year lagged value of VMT was also included to explain the behavioral inertia of VMT and to sort out short-run and long-run effects.

Unlike equation (5.3) (VMT), in equation (5.4) (MPG) fuel efficiency was considered as the endogenous variable, and was modeled as a function of gasoline price, the lagged value of fuel efficiency, and lagged value of VMT. When the fuel price is high, users try to improve the fuel efficiency of their vehicles to reduce their travel cost by purchasing more fuel-efficient vehicles or servicing their own vehicles more frequently. Therefore, the fuel price in the fuel efficiency model is an exogenous variable. The VMT can answer whether more trips lead to higher fuel efficiency or not. Moreover, to take into account the behavioral inertia of fuel efficiency, the one-year lagged value was considered in the equation. The aggregate VMT and MPG models are represented as follows:

\[
\ln VMT_t = \alpha_0 + \alpha_1 \ln Regveh_t + \alpha_2 \ln Emp_t + \alpha_3 \ln Cost_t + \alpha_4 VMT_{t-1} + \varepsilon_t \tag{5.3}
\]

\[
\ln MPG_t = \beta_0 + \beta_1 \ln Gasprice_t + \beta_2 \ln MPG_{t-1} + \beta_3 \ln VMT_{t-1} + \varepsilon_t \tag{5.4}
\]

\[\text{8 The two year lag of VMT was also tried, the results had no changes.}\]

\[\text{9 Higher fuel price encourage car manufacturers to improve fuel efficiency of their product to sell more.}\]
Empirically, the log-log specification was chosen for the general modeling approach. The log-log form did not change the relative significance of the results compared to a linear formulation. It was useful because it allowed the interpretation of the regression coefficient for each variable as the elasticity of dependent variable with respect to that predictor. In addition, this form provided the absence of heteroskedasticity\(^{10}\).

We follow the derivation of the elasticity of gasoline consumption and fuel price with respect to fuel efficiency presented in Mayo and Mathis (1988). Following this procedure and using equation (1) and (2), equations (5) and (6) were derived. Namely, the elasticity of gasoline consumption with respect to fuel efficiency \( (g_e) \) and fuel price elasticity of gasoline consumption \( (g_p) \) are:

\[
\begin{align*}
g_e &= -\left(\frac{\partial m}{\partial c}\right)\left(\frac{c}{m}\right) - 1 = -\alpha_3 - 1 \quad (5.5) \\
g_p &= \left[\left(\frac{\partial m}{\partial c}\right)\left(\frac{c}{m}\right)\left(1 - (\frac{\partial e}{\partial p})(\frac{p}{e})\right)\right] - (\frac{\partial e}{\partial p})(\frac{p}{e}) = \alpha_3(1 - \beta_1) - \beta_1 \quad (5.6)
\end{align*}
\]

Equation (5.5) states that the fuel efficiency elasticity of fuel consumption is equal to the negative elasticity of VMT with respect to fuel cost per mile minus one (Greene 1992). Equation (5.6) indicates that fuel price elasticity of fuel consumption is related to elasticity of mile traveled with respect to travel cost per mile \( (\alpha_3) \) and the elasticity of fuel efficiency with respect to the fuel price \( (\beta_1) \). Thus, to estimate the elasticities of fuel consumption, the coefficient of fuel cost per mile in VMT equation and coefficient of fuel efficiency in MPG equation were required.

\(^{10}\) Breusch-Pagan test for heteroskedasticity was performed in SAS for log-log regression results on both VMT and MPG model. Test failed to reject the null hypothesis of constant variance in the residuals (no heteroskedasticity) for both VMT and MPG.
Model Estimation

The empirical specification in this study considers VMT and fuel efficiency to be jointly determined. VMT is affected by fuel efficiency mainly through the rebound effect. According to the theoretical underpinnings of the rebound effect, the increase in VMT due to fuel efficiency increases is an income effect from the lower cost of driving per mile (Blair et al. 1984). However, over time increasing VMT can also lead to increases in fleet fuel efficiency. For example, as commuters increase the amount that they travel, they may begin to demand more fuel efficient vehicles. However, if the increase in VMT is not due to an increase in individual driving behavior, i.e. constant VMT per capita, VMT may not lead to changes in fleet fuel efficiency. By treating VMT and fuel efficiency as endogenous we are able to test for the effect that VMT has on fleet fuel efficiency. Furthermore, there is strong theoretical and empirical evidence to believe that VMT and MPG are endogenous (Binswanger 2001; Small and Van Dender 2007). If we were to treat these variables as exogenous we run the risk of overestimating the rebound effect. Therefore our model considers a system of equations describing both VMT and MPG.

The key assumption of the classical regression model is that the errors of residuals of the estimated equations should be uncorrelated (Granger and Newbold 1986; Harvey 1990). Two types of correlations were considered in the estimation process proposed by Harvey (1990):

- Synchronously correlated current errors, where residuals of different equations are correlated at a point in time.
- Serially correlated errors where a single equation’s residuals are correlated across two points in time.

In order to satisfy the first type of correlations, the VMT and MPG equations were appropriately estimated with the 3SLS method. This method combines the two-stage least squares (2SLS) method, which accounts for simultaneous equations, with seemingly unrelated regression (SUR) method that uses information in synchronously correlated residuals Harvey (1990). Following the work by Kennedy (2003) and Harvey (1990), each single equation was modeled with autoregressive correlation in 3SLS in order to release the second type of residual correlation. The 3SLS method will be explained in the following section.

3SLS

The 3SLS method improves the efficiency of parameter estimation by taking the cross-equation error correlations into consideration. A common finding in time series regression analysis is that residuals are correlated with their own lagged values. This serial correlation violates the standard assumption of regression theory, which states disturbances are not correlated with other disturbances. In this system of equations, the VMT and MPG models are time series models that might have correlation between their residuals.

Breusch-Godfrey tests on the VMT and MPG models were implemented separately. The results generated demonstrate that there is sufficient evidence to reject the null hypothesis that the VMT residual has no serial correlation at 5% significance. This indicates that the serial correlation should be considered in the VMT model. In case of
MPG, the test results indicate no serial correlation. Therefore, first order autocorrelation was implemented on the VMT model and the model specification is described below:

\[ y_t = x_t \beta + u_t \]

(5.7)

\[ u_t = \rho u_{t-1} + \epsilon_t \]

where \( y_t \) is the dependent variable, \( x_t \) is the explanatory variable, \( u_t \) is the first order serially correlated disturbance and \( 0 \leq \rho \leq 1 \) is the first order serial correlation coefficient. The coefficients of MPG and VMT equations were obtained by using the 3SLS method on the system of equations. In order to release the first order serial correlation of VMT, the parameter \( \rho \) was obtained by stacking the VMT residual regression \( (u_t) \) versus the lagged VMT residual \( (u_{t-1}) \). Then, variables of VMT model were transformed as shown below:

\[ y_t - \rho y_{t-1} = (x_t - \rho x_{t-1}) \beta + \epsilon_t \]

(5.8)

Finally, the system of equations that includes MPG and transformed VMT equations was estimated with the 3SLS method. The estimated \( \rho \) for the VMT equation is 0.573. Small and Van Dender (2007), and Babula and Corey (2004) have used 3SLS method with first order of autocorrelation for the whole system of equations without testing serial correlation for each model separately.

**Empirical results**

In Table 5.2, coefficient, standard error and t-statistic value for each variable are presented. The stationary of each estimated equation’s residuals is considered as a goodness of fit alternative besides the adjusted \( R^2 \) value (Babula and Corey 2004).
Granger and Newbold (1986) pointed out stationary equations should generate stationary residuals with no unit root. The results of the Augmented Dickey-Fuller test on each of the equation’s residuals indicated that both equations’ residuals are stationary at 5% significance level; therefore, the system of equations has been specified adequately with no unit root (Dickey and Fuller 1979).

Overall, the results lend strong support to the model. The adjusted $R^2$ in VMT and MPG model demonstrates that 96% and 97% of errors and variations are defined by explanatory variables, respectively. All coefficients have the expected signs and are significant at 95% confident level except for the coefficient associated with the employment variable in the VMT model and the VMT variable in MPG model. The employment coefficient is significant at 85% confident level. The sign of employment is logical which implies higher VMT with increase of the number of employment and economic activities. It is expected that more vehicles lead to more trips. Thus, the registered vehicle coefficient has a positive sign, which represents the direct relation between the number of registered vehicles and VMT. The change in cost of driving per mile can be explained by changes in gas price and fuel efficiency. Cost coefficient in VMT model has negative sign due to the effect of these factors on driving cost per mile. The elasticity of VMT with respect to cost per mile is -0.146.

In the VMT model, the lagged VMT variable was eliminated because it is not statistically significant and has negative side effects. The inclusion of the lagged dependent variable has undesirable side effect on employment coefficient (Greene 1992). The coefficient associated with the employment variable, which is expected to be related
to the VMT positively, would be negative and insignificant if the lagged VMT variable is included.

The MPG model also is well explained by selected independent variables. The gas price coefficient in this model is positive and significant. It clearly implies that users try to increase the fuel efficiency by purchasing more fuel-efficient vehicles or by servicing their cars frequently when the gas price increases. The MPG is elastic with respect to gas price by a coefficient of 0.025. Based on the lagged VMT coefficient, there is no effect of VMT on fuel efficiency, which demonstrates factor contributing to VMT increment is population growth not drive more per person. This is in agreement with the results of previous research by Heaslip et al. (2014) on Washington State VMT, which stated that the VMT per capita has been declining and increasing the VMT is due to the population growth. Regarding fuel efficiency improvement, VMT is not an encouraging factor for commuters whose amount of travel is decreasing over time.

Table 5.2 Model estimation results of the 3SLS method (VMT AR(1)-MPG AR(0))

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-statistic</th>
<th>Adjusted $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{LnVMT}_t$</td>
<td>$\text{intercept}$</td>
<td>2.928768</td>
<td>0.310551</td>
<td>9.43</td>
</tr>
<tr>
<td>$\text{LnVMT}_t$</td>
<td>$\text{LnEmp}_t$</td>
<td>0.248456</td>
<td>0.168454</td>
<td>1.475</td>
</tr>
<tr>
<td>$\text{LnVMT}_t$</td>
<td>$\text{LnRegveh}_t$</td>
<td>0.892899</td>
<td>0.173962</td>
<td>5.13</td>
</tr>
<tr>
<td>$\text{LnMPG}_t$</td>
<td>$\text{LnVMT}_t$</td>
<td>-0.14637</td>
<td>0.025503</td>
<td>-5.74</td>
</tr>
<tr>
<td>$\text{LnMPG}_t$</td>
<td>$\text{LnEmp}_t$</td>
<td>1.060077</td>
<td>0.763644</td>
<td>1.39</td>
</tr>
</tbody>
</table>

- The critical value of t-statistic at $\alpha = 0.05$, $\alpha = 0.1$, and $\alpha = 0.15$ are equal to 2.035, 1.692, and 1.474, respectively.
Based on equations (5) and (6), the short-run elasticities of gasoline consumption with respect to fuel efficiency and gasoline price are estimated to be -0.854 and -0.167, respectively. One-unit increase of fuel efficiency decreases the fuel consumption by 0.854 units and one-unit increase of gas price decreases the consumption by 0.167 units. It could be inferred that the gas price effect on gas consumption is not substantial. The short-run rebound effect of improving fuel efficiency is about 14.6%, which implies that 14.6% of the efficiency improvement is taken back in the form of increased vehicle miles traveled. Given the insignificance of the lagged dependent variable in the VMT equation, long-run elasticities are similar to the short-run estimates. The estimated rebound effect is in line with the results of previous studies in literature (Greene 1992; Haughton and Sarkar 1996; Jones 1993; Wirl 1997). Moreover, comparison the VMT forecasted by this model with the reported one by Washington State reveals the reliability of this model estimation.\(^{11}\)

Analysis

Both the fuel tax revenue and GHG emissions are directly proportional to fuel consumption. Therefore, precise estimation and forecasting of fuel consumption is vital in financial and environmental policy makers. A fuel consumption analysis was implemented using the estimated model (VMT/MPG). A baseline scenario is considered in which fuel consumption is predicted using forecasted values of VMT and MPG. The

\(^{11}\) 2013 VMT forecasted by model of this study is 56.89 billion, and what is reported by Washington State is around 57.21 billion (Washington State Department of Transportation, Annual Mileage and Travel Information, http://www.wsdot.wa.gov/mapsdata/travel/hpms/annualmileage.htm).
forecasted values of VMT and MPG were estimated from our model using exogenous forecasted values of the independent variables in our model. The forecasted independent variables were obtained from the Washington State Department of Transportation (WSDOT), the Transportation Revenue Forecast Council (2012), and Economic and Revenue Forecast Council (2012). In addition to our baseline model, in order to investigate the relative importance and the effect of various exogenous factors, we performed a sensitivity analysis of our forecasts by fixing one variable at a time to 2011 levels. Our baseline forecasts, as well as the sensitivity of our forecast to each independent variable are depicted in Figure 2. Our forecasted values for fuel consumption were most sensitive to the number of registered vehicles.

\[ \Delta g = g \cdot g_e \cdot a \]  

(5.9)

where:

- \( g \): Fuel consumption
- \( \Delta g \): Fuel consumption loss
- \( g_e \): Fuel consumption elasticity with respect to fuel efficiency
- \( e \): Fuel efficiency
- \( a = \frac{\Delta e}{e} \)

The rebound effect is an elasticity by definition, and with respect to fuel consumption it acts like a constant of proportionality that decreases impact of fuel efficiency improvement on fuel consumption. For example, using the estimated rebound
effect in this study of 14.6%, if fuel efficiency increases by 60%, the reduction in fuel consumption would only be 51.24%.

Figure 5.2 presents fuel consumptions forecasted for different scenarios. In the absence of fuel efficiency improvements, fuel consumption is expected to increase. Therefore, improving fuel efficiency could be a significant factor in controlling future fuel consumption. Likewise if fuel prices remain constant or fall future fuel consumption will likely increase as well. In the estimated model, the increasing the gasoline price would spur increases in fuel efficiency, while simultaneously decreasing VMT. Both of these effects cause a decrease in fuel consumption. In addition, higher fuel price motivates car manufacturers to produce more fuel-efficient vehicles to sell more, which increases the aggregate fuel efficiency and mitigates fuel consumption. According to the estimated model, higher employment and increasing the number of registered vehicles increase VMT. This leads to greater fuel consumption. Since our forecasts are the most sensitive to the number of registered vehicles (representative of population), it could be the most influential variable in the growth of fuel consumption. Hence, in order to control the fuel consumption and decrease its rate of growth, implementing programs those encourage public transportation, bicycling, and other alternative modes of transportation should be conducted seriously.

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12 Estimated rebound effect is 14.6%; therefore, 51.24% = 60% *(1-14.6%)
Revenue analysis

Fuel tax revenue is the income gained by the government through taxation on fuel. By improving the fuel efficiency, fuel consumption decreases, and thus decreases tax revenue. The potential loss of fuel tax revenue due to fuel efficiency improvements was estimated. The increase in the tax rate needed to compensate for this loss of revenue was then calculated. Table 3 presents the predicted lost revenue due to fuel efficiency gains between 2012 and 2031 assuming a fuel tax of $0.39 per gallon. The results present that in 2031 the Washington State will lose 106 million dollars due to fuel efficiency improvement, considering uncertainty interval the loss in 2031 will be between 70 and 143.5 million dollars by 95% confidence. These results are based on the difference between the baseline scenario and fixed MPG scenario. One way that governments can combat falling revenue due to fuel efficiency improvements is to increase the tax rate.

![Figure 5.2 Fuel consumption forecast in different scenarios](image)
Two approaches are considered to calculate the required increase in the fuel tax rate to offset losses due to efficiency improvements.

In the first approach, the new fuel tax rate was estimated by comparing revenue of the baseline scenario with the fixed MPG scenario. In this approach, controls affecting fuel consumption are forecasted exogenously from the model. These forecasted values are then used as the inputs of the baseline model to obtain forecasted values of VMT and MPG. These forecasted values of VMT and MPG were then used to calculate the forecasted revenue from fuel taxes. A similar approach is used to forecast tax revenues in a model where MPG is held constant at 2011 levels. The difference between the baseline model and fixed MPG model forecasts gives an estimate of the effect of fuel efficiency improvements over time on tax revenues. This information is then used to calculate the required tax rate increase necessary to offset the lower tax revenue in the baseline model due to fuel efficiency improvements.

In the second approach the impact of fuel efficiency on fuel consumption and thus revenue is estimated solely with the elasticity of VMT with respect to MPG. This approach differs from the first approach in that it invokes a ceteris paribus assumption, i.e. all of the control variables are held constant at 2011 levels. In the first approach higher population, employment, and registered vehicles, leads to larger tax revenues than observed in this approach. In this approach, it is assumed that fuel efficiency (e) improves by $a\%$ with respect to 2011 fuel efficiency, considering other factors to be fixed after 2011. The goal is to investigate the required increase in fuel tax in order to have the same level of tax revenue. Improving the fuel efficiency by $a\%$ per year decreases the fuel
consumption \( g \) by \( g_e \)\% per year; therefore, the required increase in the fuel tax to offset the change in fuel consumption is:

\[
y = \left( \frac{1}{1 + g_e} \right)
\]

\( \text{(5.11)} \)

\[
(1 + g_e) g_y \text{tax} = g \text{tax}
\]

\( \text{(5.10)} \)

Table 5.3 Fuel efficiency effect on revenue

<table>
<thead>
<tr>
<th>Year</th>
<th>Fuel consumption reduction (Million gallon)</th>
<th>Revenue loss (Million dollars)</th>
<th>95% Uncertainty interval of revenue loss (Million dollars)</th>
<th>Tax increment approach 1</th>
<th>Tax increment approach 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>34.70</td>
<td>13.53</td>
<td>-25.52</td>
<td>51.08</td>
<td>1.013</td>
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<td>2013</td>
<td>66.95</td>
<td>26.11</td>
<td>-13.34</td>
<td>63.26</td>
<td>1.026</td>
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<tr>
<td>2014</td>
<td>96.64</td>
<td>37.69</td>
<td>-1.95</td>
<td>74.64</td>
<td>1.037</td>
</tr>
<tr>
<td>2015</td>
<td>122.45</td>
<td>47.76</td>
<td>8.02</td>
<td>84.62</td>
<td>1.046</td>
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<tr>
<td>2016</td>
<td>145.03</td>
<td>56.56</td>
<td>16.81</td>
<td>93.41</td>
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<td>2017</td>
<td>166.87</td>
<td>65.08</td>
<td>25.36</td>
<td>101.96</td>
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<td>2018</td>
<td>185.19</td>
<td>72.22</td>
<td>32.54</td>
<td>109.14</td>
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</tr>
<tr>
<td>2019</td>
<td>197.68</td>
<td>77.09</td>
<td>37.45</td>
<td>114.05</td>
<td>1.071</td>
</tr>
<tr>
<td>2020</td>
<td>206.70</td>
<td>80.61</td>
<td>41.03</td>
<td>117.64</td>
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<td>2021</td>
<td>215.07</td>
<td>83.88</td>
<td>44.36</td>
<td>120.96</td>
<td>1.076</td>
</tr>
<tr>
<td>2022</td>
<td>222.17</td>
<td>86.65</td>
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<tr>
<td>2023</td>
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</tr>
<tr>
<td>2024</td>
<td>232.83</td>
<td>90.80</td>
<td>51.47</td>
<td>128.07</td>
<td>1.080</td>
</tr>
<tr>
<td>2025</td>
<td>237.37</td>
<td>92.57</td>
<td>53.29</td>
<td>129.89</td>
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<td>2026</td>
<td>241.22</td>
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<tr>
<td>2027</td>
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<td>2028</td>
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<td>2030</td>
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<td>2031</td>
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<td>105.90</td>
<td>66.92</td>
<td>143.52</td>
<td>1.087</td>
</tr>
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</table>
It should be noted that the percentage of fuel efficiency improvement in the future years was estimated from the MPG model developed. It is obvious that the required increase in the tax rate in second approach will be greater than that in the first approach. This result is due to population growth and higher economic activities over time leading to greater VMT in the first approach, and thus higher fuel consumption. The greater fuel consumption in the first model leads to more revenue. Thus a larger increase in the fuel tax rate is required to provide infrastructure to accommodate the increased demand due to efficiency improvements in the second model. The results demonstrate that the fuel tax at 2031 should be increased by 8.7% to offset revenue loss from fuel efficiency improvements in approach 1. The results from approach 2 suggest that in 2031 the fuel tax rate should be raised by 9.6% compared to current rates to offset the fuel tax revenue losses due to increased fuel efficiency.

**GHG emissions analysis**

Transportation alone produces a third of the total US GHG emissions (Morrow et al. 2010). The GHG emissions are directly related to the fuel consumption, and any change in fuel consumption affects GHG emissions. According to the Energy Information Administration (EIA 2011), a gallon of gas contains, on average, 2.421 kilograms of carbon, which is enough to produce 8.877 kilograms (19.5 lbs.) of $CO_2$. Information about the fuel consumption, which was estimated from the VMT and fuel efficiency models, was used to compute the approximate amount of $CO_2$ productions. In order to show the effect of fuel efficiency improvement on future GHG emissions, the real GHG emission in future was compared with the alternative scenario, in which the fuel
efficiency has not growth after 2011. The results in Table 5.4 show the tangible $CO_2$ reduction with the improvement of fuel efficiency over time, as well as 95% uncertainty interval of reduction. However, it is noted that the emission will be increased under the influence of increasing number of registered vehicles and employment.

Table 5.4 Fuel efficiency effect on $CO_2$ emissions (Billion pounds)

<table>
<thead>
<tr>
<th>Year</th>
<th>Forecasted $CO_2$</th>
<th>Forecasted $CO_2$ without MPG improvement</th>
<th>MPG effect on $CO_2$ reduction (%)</th>
<th>95% Uncertainty interval of $CO_2$ reduction (%)</th>
<th>Lower level</th>
<th>Upper level</th>
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<td>52.93</td>
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<td>54.26</td>
<td>4.60</td>
<td>0.74</td>
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<tr>
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<td>2017</td>
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<td>6.18</td>
<td>2.32</td>
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<tr>
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<td>53.35</td>
<td>56.96</td>
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<tr>
<td>2027</td>
<td>58.61</td>
<td>63.42</td>
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<td>8.71</td>
<td>5.33</td>
<td>12.19</td>
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</tbody>
</table>

Summary and Discussion

The core purpose of this study was to estimate the potential loss of fuel tax revenue and decrease in GHG emissions resulting from increasing fuel efficiency. The study estimated the elasticities of fuel consumption with respect to fuel efficiency and
fuel price and also the rebound effect. The model estimation was based on the annual time series data for Washington State over the time period of 1976-2011. The model was estimated as a system of equations with both VMT and MPG as endogenous variables to take into account of the simultaneous effect of VMT and MPG on each other. While MPG acts as an exogenous variable in VMT equation through fuel cost per mile, it is influenced by fuel price and VMT in the MPG equation. Lagged VMT was included in MPG equation because it is possible that commuters who drive more try to increase their fuel efficiency more than other commuters. The results show that the lagged VMT variable is not statistically significant in the MPG equation, which implies that fuel efficiency depends primarily on gas prices rather than increasing trips per person. This result is in agreement with the results of the fuel consumption analysis, which identified the number of registered vehicles as the most important factor in fuel consumption because the number of registered vehicles as the proxy of population increases fuel consumption through larger VMT.

Fuel consumption analysis shows the relative importance of different exogenous variables. We find that improved fuel efficiency and higher gasoline prices are associated with reduced fuel consumption. However, the number of registered vehicles (representative of the population) and employment (representative of economic activity) are relatively more influential than either of these factors. Accordingly, travel demand management (TDM) strategies can help people use the transportation system more efficiently, while reducing fuel consumption and vehicles GHG emissions. These strategies include such activities as eliminating or shortening trips, changing the travel
mode, as well as action that increase transportation system efficiency through carpooling, vanpooling, transit, bicycling and walking.

We estimate that, compared to current fuel usage rates, the trend in improved fuel efficiency would be associated with Washington State fuel tax revenue loss of 106 million dollars at 2031. To forecast fuel tax changes, two different approaches were considered. The first approach investigates the effect of fuel efficiency on fuel tax revenue, accounting for other explanatory variables. Current fuel tax would need to increase by 8.7% to replace the loss resulted by fuel efficiency improvement at 2031. The second approach isolated the effect of other explanatory variable effects on fuel tax revenue. While increases in the number of registered vehicles and employment are expected to increase future fuel consumption and fuel tax revenue, this second approach ignores these effects and considers only the elasticity of fuel consumption with respect to fuel efficiency. This approach is based on the required revenue with respect to given demographic and economic conditions. It was demonstrated that to restitute the fuel tax revenue loss, the fuel tax should be increased by 9.6%. The tax increment resulted by the second approach is the suggestion of this study. One of the suggested policies to increase revenue through registration tax on new vehicles or vehicles plate fee for vehicles with high fuel economy or alternative fuels.

While increasing the number of registered vehicles and increased economic activity are expected to increase GHG emissions, improving fuel efficiency will tend to decrease CO₂ produced from burning fuel. We estimated that fuel efficiency improvements will decrease these emissions by 8.7% in 2031.
References


Electric vehicles are a type of the green vehicles, which are more environmentally friendly than the traditional petroleum combustion engine, and other alternative fuel vehicles. Increasing the usage of electric vehicles is one of the principal policies to decrease the aggregate fuel consumption and greenhouse gas (GHG) emissions to mitigate the causes of climate change. In order to increase the attraction of electric vehicles for consumers, governments have employed a number of incentives. In this study the relationship between shares of electric vehicle and presence of incentives as well as other influential socioeconomic factors on electric vehicle shares were examined. Methodology of this study is based on the cross-sectional time-series analysis. The developed model is an aggregated binomial logit share model that estimates the modal split between EV and conventional vehicles for different U.S. states from 2003 to 2011. The model was estimated using different panel data methods and the results were compared. The results demonstrated that the electricity prices with negative correlation, urban roads and incentives with positive correlation are significant factors on states’ electric vehicle market share. Sensitivity analysis results suggested that of these factors electricity price affects electric vehicle adoption rate the most. According to the sensitivity analysis of electric vehicle adoption rate, state of Vermont has the most sensitivity with respect to electricity price and New Jersey is the most sensitive state with
respect to urban roads and incentives. Moreover, the time trend model analysis found that the electric vehicle adoption has been increasing over time, which is parallel with diffusion of new technology theory.

Introduction

The United States’ dependency on foreign oil has been growing to meet the petroleum demand. Higher dependency results in some national and economical issues. The US transportation sector has always been the major consumer of energy, which uses around 71% of petroleum (US Energy Information Administration, 2012). High gasoline consumption in the US transportation sector not only raises concerns regarding national energy security, but also poses many questions regarding the environmental impacts of greenhouse gases emissions.

Electric vehicles are one type of green vehicles, which are more environmentally friendly than traditional petroleum combustion engine and other alternative fuel vehicles (Pesaran and Johnson 2002). Two important advantages of electric vehicles (EV) are lower driving costs and greenhouse gas emissions. The well-to-wheel efficiency of electric cars is around 1.15 kilometer per million Joule (km/mJ), while the efficiency of celebrated hybrid model (Toyota Prius) is estimated around 0.56 km/mJ and much lower for conventional cars (Toyota Camry, 0.28 km/mJ) (Eberhard and Tarpening 2006; Nia and Ghamami 2013; Romm 2006). Moreover, electric cars have zero local emissions at the point of operation and low global emissions; therefore, increasing the use of electric
vehicles contributes significantly to reduction of air pollution (Samaras and Meisterling 2008).

Despite these advantages, the rate of EV adoption is slow without stimulation from external factors such as strict emissions regulations, fuel price increment, or financial incentives (Eppstein et al. 2011; IEA 2013; Shafiei et al. 2012). Factors such as lack of knowledge by potential adopters, low consumer risk tolerance, and high initial production cost are common barriers to any new technology (Argote and Epple 1990; Jaffe and Stavins 1994; Stoneman and Diederen 1994). To overcome these barriers, different states have established a number of consumer incentives for adopting EVs. Some states offer incentives as credit and rebate and some such as California, New York, Florida allow EV owners to use the high occupancy vehicle (HOV) lane with no restriction. These policies could be influential on environment and aggregate fuel usage through their effect on EV shares.

Literature reviews on effect of incentives on adoption of alternative fuel vehicles present conflicting results. While some studies have demonstrated the positive effect of financial incentives on hybrid electric vehicles’ (HEV) sales (Beresteanu and Li 2011; Gallagher and Muehlegger 2011), others demonstrated that incentives have no effect on HEV adoption (Diamond, 2009). Sierzchula et al. (2014) found financial incentives to be significantly and positively correlated to country’s EV market share, whereas Zhang et al. (2013) showed insignificant relation between financial incentives and people’s willingness to buy EVs. Thus, besides incentives, analyzing other factors affecting electric vehicles share is imperative.
However, little has been done, on the significant factors influencing EV share in the United States. The purpose of this study is to examine and analyze the significance and strength of state incentives and other significant socioeconomic factors in promoting EV adoption. As a primary methodology, cross-sectional time-series analysis of number of EV statistics over time from US states was used to test the relationship between EV adoption and variety of variables. The EV data for a period of 9 years (from 2003 to 2011), for 19 states with no missing data was collected from U.S. Energy Information Administration (EIA). The available EV data are aggregated number of EV for different states over time. The developed model is an aggregated binomial logit share model that estimates the modal split between EV and conventional vehicles for different states of the U.S. over time. In this model, we explicitly incorporated various factors as explanatory variables in the utility function in order to quantify their effect on EV adoption rates. These explanatory variables include income, vehicle miles traveled (VMT), electricity price, gasoline price, urban area and incentives.

Methodology

The methodology for this study is based on development of the modal split model between electric vehicles and other fuel type vehicles (mainly conventional vehicles). The annual share of electric vehicle as an aggregate data is considered as the dependent variable, with a value between 0 and 1.
Macroscopic cross-sectional logit model

Due to the aggregate dataset available, a macroscopic logit market share model is developed to demonstrate the mode choice decisions between electric vehicles and conventional vehicles. The market share model reduces to a utility function, state market share, which is a function of a number of independent vehicle type characteristics, socioeconomic and policy variables that are varies over states. The EVs share variations over states (in addition to their variation over time) helps separate and examine the different determinant factors of adoption that vary across states but are correlated in time. On a state level, consumers’ preferences for different vehicle type choices are affected by a number of predictor variables that vary, on average by state that affect consumer utility. The states monetary considerations include the average income per capita, (Income variable, which is considered as effective consumer discount rate for future energy cost saving, and risk tolerance for new technologies) (Diamond 2009), gasoline price (gasprice variable), electricity price (Eprice variable) and annual miles traveled (VMT variable which is related to annual cost of fuel). Non-monetary factors include government incentive (Incentive variable), which increases utility of EV, HOV-lane privilege (HOV variable) which provide a benefit to the consumer via convenience, rate of Urban road (Urban variable), which present the rate of urban road with respect to total roads millage in states. As such, the final specification of the utility function for EV in state $i$ at time $t$ can be defined as:

$$U_{Eit} = F(Income_{it}, Gasprice_{it}, Eprice_{it}, VMT_{it}, Incentive_{it}, HOV_{it}, Urban_{it})$$  \hspace{1cm} (6.1)
We define $P_{Eit}$ as the share of EV and $P_{0it}$ as the share of conventional fuel type vehicles EV in state $i$ at time point $t$ in such a way that $P_{Eit} + P_{0it} = 1$. These fractions can be developed as follows (Bierens 2004; Gruca and Sudharshan 1991):

$$P_{Eit} = \frac{e^{U_{Eit}}}{1 + e^{U_{Eit}}}$$

(6.2)

Then, to solve and estimate different coefficient of the utility function the fraction model can be transformed as below:

$$\ln \left( \frac{P_{Eit}}{P_{0it}} \right) = \ln \left( \frac{P_{Eit}}{1-P_{Eit}} \right) = U_{Eit} = \alpha + \beta_1 \text{Income}_{it} + \beta_2 \text{Gasprice}_{it} + \beta_3 \text{Eprice}_{it} +$$

$$\beta_4 \text{VMT}_{it} + \beta_5 \text{Incentive}_{it} + \beta_6 \text{HOV}_{it} + \beta_7 \text{Urban}_{it}$$

(6.3)

This equation takes a generalized linear form and its coefficient can be estimated via linear regression. The coefficients of this linear model will be estimated without transforming to log-log model because the left hand side of the utility function in equation (6.3) is negative.\(^{13}\)

Model definition is based on the identifying the effective factors on EV’s utility improvement and adoption versus conventional vehicle. It is clear that the variables with positive sign encourage the use of EVs and increasing the value of variable with negative

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\(^{13}\) Due to the negligible EV share with respect to conventional vehicles the fraction in the parentheses is very small, therefore the value of $\ln \left( \frac{P_{Eit}}{1-P_{Eit}} \right)$ is negative.
sign increase the use of conventional vehicle. The estimation of the model in this study is accomplished based on the set of panel data over United States.

Panel data regression model

The panel data regression was chosen for the analysis of EV adoption because this methodology provides various benefits and overcomes some of the limitations of time-series and cross-section studies (Kennedy 2003). Panel data can deal with heterogeneity resulted from variation of some unmeasured explanatory variables that affect the behavior of people of different states. It also overcomes the problem of omitted time-series variables that influence the behavior of people in different states uniformly, but differently in each time period. Panel data alleviates multicollinearity problem by creating more variability through combining the variation across states with variation over time. The equation for a panel data regression is (Washington et al. 2011):

\[ Y_{it} = \alpha + X_{it} \beta + u_{it} \]  \hspace{1cm} (6.4)

where \( i \) refers to the cross-sectional units (states), \( t \) refers to the time periods, \( Y_{it} \) is dependant variable, \( \alpha \) is constant, \( X_{it} \) is the set of explanatory variable, \( \beta \) is the coefficients of explanatory variables, and \( u_{it} \) is error of residuals. One-way and two-way error component models for disturbances are specified respectively as follows:

\[ u_{it} = \mu_i + v_{it} \]  \hspace{1cm} (6.5)

and

\[ u_{it} = \mu_i + \lambda_t + v_{it} \]  \hspace{1cm} (6.6)
Where $\mu_i$ is the unobserved cross-sectional specific effect, $\lambda_t$ is the unobserved time effect, and $v_{it}$ is the random disturbances. There are two different approaches to estimate various parameters of the model; fixed effect and random effect. When $\mu_i$ and $\lambda_t$ are assumed to be fixed parameters that needs to be estimated and remainder random disturbances $v_{it}$ are independent and identically distributed such that $v_{it} = IID(0, \sigma_v^2)$, the model is called fixed effect, and when $\mu_i$ and $\lambda_t$ as well as $v_{it}$ are considered as random such that $\mu_i = IID(0, \sigma_\mu^2)$, $\lambda_t = IID(0, \sigma_\lambda^2)$, $v_{it} = IID(0, \sigma_v^2)$ and $\mu_i$ and $\lambda_t$ are independent of the $v_{it}$, the model is called random effect (Baltagi 2008).

Data

In order to develop the model of equation (6.3), data from various sources had to be merged into one usable data set. Department of Energy, Energy Efficiency, and Renewable Energy Division have recorded the number of EVs in use over different states from 2003 to 2011. The statistical analysis used data from the following states: Arkansas, Alabama, Arizona, California, Colorado, Florida, Georgia, Illinois, Massachusetts, Michigan, North Carolina, New Jersey, New York, Ohio, Oklahoma, Oregon, Tennessee, Vermont, and Wyoming. These states are selected because available data for these 19 states has no missing record over this period of time. The dependent variable in the developed model is the logarithm of annual state EV share, which is defined as number of EVs in use as a percentage of all registered vehicles in the state for that same time period. The annual number of registered vehicles was obtained from Federal Highway Administration (FHWA 2003-2001). The incentive variable in this study is a dummy
variable that considers statewide tax incentives, rebates and other benefits. In order to convert these data to a monetary value, the price of electric vehicles over time is needed. Based on the data availability on electric vehicles price, this study only considered if states provide incentives on EVs or not (1 or 0). The HOV dummy variable demonstrates whether there is a HOV restriction exemption for EVs on one or more major highways in a state. Table 6.1 presents the descriptive statistics for selected variables and data sources used in this study.

Estimation Results

Table 6.2 presents the results of regression on developed model. Statistical Software SAS was used in this analysis to estimate the intercept and coefficients of the model. Three different types of effects; between-, fixed- and random-effects were considered to estimate the panel data model. The between-effect regression measures only the impact of the cross-sectional (states) variances on EVs shares. It runs a single multivariate regression on the set of states EV shares against the set of independent variables. All dependent and independent variables in each state’s equation are averaged over time. Looking at the between-effect regression results, negative intercept implies that everything else being equal, conventional vehicle is more likely to be chosen. Average vehicle miles traveled (VMT) per capita was significant with positive coefficient, indicating more EV shares for states with higher VMT per capita.
<table>
<thead>
<tr>
<th>State</th>
<th>EV share</th>
<th>Income</th>
<th>VMT</th>
<th>Gas price</th>
<th>E price</th>
<th>Urban</th>
<th>Incentive</th>
<th>HOV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>STD</td>
<td>Mean</td>
<td>Mean</td>
<td>STD</td>
<td>Mean</td>
<td>STD</td>
<td>Mean</td>
</tr>
<tr>
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<td>41380.30</td>
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<td>8216.93</td>
<td>2183.69</td>
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<td>301.50</td>
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<td>14842.58</td>
<td>3505.93</td>
<td>2.22</td>
<td>0.57</td>
</tr>
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<td>3390.11</td>
<td>1272.95</td>
<td>33444.44</td>
<td>2596.20</td>
<td>11268.12</td>
<td>3034.97</td>
<td>2.31</td>
<td>0.49</td>
</tr>
<tr>
<td>California</td>
<td>27603.37</td>
<td>7165.77</td>
<td>40944.44</td>
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<td>2564.79</td>
<td>2.43</td>
<td>0.57</td>
</tr>
<tr>
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<td>197.67</td>
<td>92.87</td>
<td>40400.00</td>
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<td>11165.57</td>
<td>3113.42</td>
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<td>441.02</td>
<td>37355.56</td>
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<td>3272.61</td>
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<td>33966.67</td>
<td>1971.04</td>
<td>13722.22</td>
<td>3747.59</td>
<td>2.14</td>
<td>0.56</td>
</tr>
<tr>
<td>Illinois</td>
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<td>40233.33</td>
<td>3298.11</td>
<td>9531.11</td>
<td>2342.15</td>
<td>2.29</td>
<td>0.57</td>
</tr>
<tr>
<td>Massachusetts</td>
<td>2906.00</td>
<td>1128.37</td>
<td>48188.89</td>
<td>4577.24</td>
<td>9628.77</td>
<td>2418.18</td>
<td>2.33</td>
<td>0.56</td>
</tr>
<tr>
<td>Michigan</td>
<td>2442.78</td>
<td>1321.82</td>
<td>34088.89</td>
<td>1823.76</td>
<td>11516.03</td>
<td>3951.83</td>
<td>2.25</td>
<td>0.55</td>
</tr>
<tr>
<td>North Carolina</td>
<td>678.78</td>
<td>609.81</td>
<td>33744.44</td>
<td>2500.06</td>
<td>12671.62</td>
<td>3312.93</td>
<td>2.30</td>
<td>0.58</td>
</tr>
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<td>New Jersey</td>
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<td>48244.44</td>
<td>4255.89</td>
<td>9598.46</td>
<td>2418.20</td>
<td>2.24</td>
<td>0.56</td>
</tr>
<tr>
<td>New York</td>
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<td>1547.81</td>
<td>45488.89</td>
<td>5140.88</td>
<td>8010.00</td>
<td>2130.53</td>
<td>2.34</td>
<td>0.57</td>
</tr>
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<td>Ohio</td>
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<td>163.03</td>
<td>34666.67</td>
<td>2554.41</td>
<td>10931.11</td>
<td>2620.81</td>
<td>2.30</td>
<td>0.57</td>
</tr>
<tr>
<td>Oklahoma</td>
<td>139.22</td>
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<td>3741.04</td>
<td>1483.66</td>
<td>3822.29</td>
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</tr>
<tr>
<td>Oregon</td>
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<td>561.65</td>
<td>34531.11</td>
<td>2553.65</td>
<td>10633.37</td>
<td>2874.82</td>
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<td>0.57</td>
</tr>
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<td>Tennessee</td>
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<td>33488.89</td>
<td>2413.22</td>
<td>13049.53</td>
<td>3307.00</td>
<td>2.03</td>
<td>0.56</td>
</tr>
<tr>
<td>Vermont</td>
<td>429.22</td>
<td>239.59</td>
<td>37587.68</td>
<td>3603.41</td>
<td>13956.00</td>
<td>3543.08</td>
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<td>0.59</td>
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<tr>
<td>Wyoming</td>
<td>39.44</td>
<td>23.40</td>
<td>42797.56</td>
<td>5595.99</td>
<td>19845.97</td>
<td>5047.67</td>
<td>2.25</td>
<td>0.55</td>
</tr>
</tbody>
</table>

**Sources**
- U.S. Energy Information Administration, Office of Energy Consumption and Efficiency Statistics provided number of electric vehicle, US Department of Transportation Annual Highway Statistics (2003-2011)
- US Census Bureau
- US Department of Transportation Annual Highway Statistics (2003-2011)
- US Energy Information Administration State Energy Data 2012: Prices and Expenditures
- US Energy Information Administration State Energy Data 2012: Prices and Expenditures
- US Department of Transportation Annual Highway Statistics (2003-2011)
- Incentive data from the Department of Energy, Energy Efficiency and Renewable Energy Division (DOE EERE)
- Incentive data from the Department of Energy, Energy Efficiency and Renewable Energy Division (DOE EERE)
Gasoline price was significant and had positive effect on EV use in different states. Since higher gasoline price increases the conventional vehicles’ trip cost, the willingness of EV adoption is more in state with higher gasoline price. Urban roads variable is one of the factors that have positive effect on using EVs. The use of EV in states with more urban roads is higher, because over 78% of U.S. urban commuters travel less than 40 miles per day, which is perfect for the range of today’s EVs (Dennis 2007). The urban road coefficient is positive and strong enough to affect the states’ EV shares. Averaged over time, the effect of incentives was significant in encouraging people to adopt EV in different states. The model shows that the HOV exemption privilege is not tempting enough to convince people to adopt EVs instead of conventional vehicles. Most surprising results were the unexpected effects of per-capita income and electricity price on EV shares, which could be due to the lack of information about the impact of time-dependent variables. Between-effects regression method neglects the effect of time on the cross-sections. Therefore, there is a potential omitted variable bias due to isolating the effect of time on variables.

Between-effects regression results present the relationship between the EV shares and different socioeconomic characteristics and incentive of a particular state without considering the impact of each variable over time. Due to the unreliable effect of income and electricity price on EV shares, the result of this model is not satisfying. In addition, adoption rate of a new technology changes over time due to diffusion-related effects, which is not considered in this model. Therefore, to control the omitted variable bias and to cover time-dependent effects, the fixed-effect regression was ran on this model.
Fixed effect models

The one-way fixed-effects regression catches cross-sectional variances by defining unobservable specific effect for each state, while considering the impact and significance of each explanatory variable over time, averaged across all the states (Stock and Watson 2003). All the variables have proper sign except HOV, which is not significant and it can be ignored. The income per capita is positive and significant, representing the increase of EV shares with income growth over time. Comparing with between-effects model, VMT per capita and gasoline price have lost their significance. According to basics of one-way fixed-effects model, which considers variations of EV
shares over time, it can be concluded that variations of VMT per capita and gasoline price are significant over states but not over time.

Electricity price has proper sign, indicating decrease of utility of EVs for higher electricity price. Urban road is an important factor that has positive effect on EV adoption. Incentive is a significant factor and increases the use of EVs. It demonstrates that establishing more incentives encourages people to use EVs over time.

In addition to predefined significant explanatory variables (such as income per capita, electricity price, urban roads, and incentives), there are some unobservable factors that are estimated for each state separately. Impact and magnitude of unobservable factors on each specific state is introduced by state fixed effect\textsuperscript{14} as dummy variables. The time-averaged values of income per capita, electricity price, urban roads, and incentives are presented for different states in Figures 6.1-6.5. These figures can show the impact of unobservable factors more clearly. For instance, comparing different explanatory variables for two states of Vermont and New Jersey without considering the unobservable factors can mislead the judgment on number of EV use in each state. Vermont has less income, fewer urban roads, fewer incentives, and higher electricity prices compared to New Jersey, which could imply considerable more EVs in New Jersey, but this is not true. The positive specific fixed effect for state of Vermont, and negative specific fixed effect for New Jersey State mean that there are some unobservable factors.

\textsuperscript{14} States fixed effect: AK=1.891031, AL=0.936412, AZ=1.179288, CA=0.603667, CO=-0.57697, FL=-4.5447, GA=-0.17692, IL=-2.83505, MA=-3.10951, MI=0.70166, NC=-0.92404, NJ=-6.09443, NY=1.838628, OH=-2.21032, OK=-1.33355, OR=1.339569, TN=-1.30497, VT=5.336568
factors, which encourage Vermont people and discourage New Jersey people to use more EV.

**Figure 6.1** Average value of number of electric vehicles in use

**Figure 6.2** Average value of income per person

**Figure 6.3** Average value of electricity price gasoline gallon equivalent
Besides the state specific effects, different time points may affect the share of EV. In some cases natural phenomenon, economy crash or some specific events may shock the market share and would change the share of EVs. In order to investigate these effects besides state specific effects, two-way fixed-effects regression was accomplished. The time specific fixed effects are interpreted similar to the state specific fixed effects and intercept of model. It means that their negative signs imply more interest and likelihood.
of using conventional vehicles over EVs at corresponding time points. The least fixed effect values are observed in years 2005, 2006 and 2008, respectively\textsuperscript{15}.

The lower interest of people in adopting EV at 2005 and 2006 would be explained by Hurricane Katrina. However, the Hurricane Katrina increased the gasoline price. Considering the negligible effect of gasoline price on EV shares, increase of gasoline price did not increase the utility of EVs. On the other hand, based on the disruptions on socio and economic conditions resulted by hurricane in 2005, people hardly ever chose to adopt EVs. The 2006 fixed effect is less negative than 2005, indicating that the effect of this phenomena was continued through 2006 with lower impact. Economic recession in 2008 is another circumstance that had negative impact on people’s decision to adopt EVs or not. Due to poor economic condition in 2008, people could not afford higher initial purchase price of EVs.

**Random-effect models**

The process of random-effects model is similar to the fixed-effects model in that it postulates a different intercept for each state and/or time, but it intercepts different intercepts as having been drawn from a bowl of possible intercepts. Therefore, these intercepts may be interpreted as random and treated as though they were a part of the error term. The coefficients resulted from one-way and two-way random-effects estimation methods are mostly acceptable in sign; however, the electricity price and urban roads are the only significant variables in both methods.

\textsuperscript{15} Time point fixed effect: 2003= 0.77, 2004= 0.43, 2005= -0.16, 2006= -0.13, 2007= 0.10, 2008= -0.43, 2009= 0.74, 2010= 0.32.
Trends over time

One of the major factors in adoption of new technology is time. People awareness and knowledge on new technology has been growing by time. It means that over time the innovators influence imitators to switch to EVs. To catch the impact of time trends on EV shares, the one-way fixed-effects estimation method, considering a time trend variable, was applied. The two-way fixed-effects regression wipes out the effect of time trend because same values were used for each state. The results represent the rational sign for all variables except HOV (same as other regression methods). Electricity price, urban roads and time trend variables are significant factors. The sign and strength of the time trend variable demonstrates the importance and influence of time in convincing people to adopt EVs as a new technology. Note that the adjusted R² of this result is more than the one without time trend variable, which can validate the impact of time trend on EV diffusion. In addition to increasing the knowledge of individuals about new technology over time, the variety of available models of EVs (over time) can encourage and increase the adoption rate of EVs.

Sensitivity Analysis

Sensitivity analysis was conducted in order to test the base model’s overall robustness and sensitivity of different variables (specifically electricity price, urban roads, and incentives). The one-way fixed-effects model is considered as a base model to present the impacts of different explanatory variables variations. The variations of model’s goodness of fit (explanatory power) and fixed effect factors with the removal of
electricity prices, urban roads, and incentives variables, are demonstrated in Models 1-4. The model’s number is identified based on the individual variable(s) in which explored through sensitivity analysis e.g., electricity prices in Model 1.

Table 6.3 Sensitivity analysis models 1-4

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficients (standard error)</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercep</td>
<td></td>
<td>-11.03*** (1.6755)</td>
<td>-11.96*** (1.64)</td>
<td>-11.97*** (4.27)</td>
<td>-10.78 (0.64)</td>
</tr>
<tr>
<td>Income</td>
<td></td>
<td>-8.63E-6 (49E-6)</td>
<td>9.5E-5 (5.2E-5)</td>
<td>7.6E-5 (5.2E-5)</td>
<td>-</td>
</tr>
<tr>
<td>VMT</td>
<td></td>
<td>3E-5*** (24E-6)</td>
<td>2.3E-6 (2.3E-5)</td>
<td>7.22E-6 (2.3E-5)</td>
<td>1.8E-5 (2.3E-5)</td>
</tr>
<tr>
<td>Electric price</td>
<td></td>
<td>-</td>
<td>-3.26*** (0.91)</td>
<td>-3.37*** (0.9)</td>
<td>-</td>
</tr>
<tr>
<td>Gasoline price</td>
<td></td>
<td>0.029 (0.292)</td>
<td>0.207 (0.279)</td>
<td>0.14 (0.27)</td>
<td>0.21 (0.13)</td>
</tr>
<tr>
<td>Urban</td>
<td></td>
<td>8.25*** (4.346)</td>
<td>-</td>
<td>10.16*** (4.18)</td>
<td>-</td>
</tr>
<tr>
<td>HOV</td>
<td></td>
<td>-0.665* (0.4)</td>
<td>-0.36 (0.39)</td>
<td>-0.25 (0.38)</td>
<td>-0.53 (0.38)</td>
</tr>
<tr>
<td>Incentive</td>
<td></td>
<td>0.296 (0.315)</td>
<td>0.42 (0.3)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>R²</td>
<td></td>
<td>0.7503</td>
<td>0.7645</td>
<td>0.77</td>
<td>0.7431</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td></td>
<td>0.709</td>
<td>0.725</td>
<td>0.733</td>
<td>0.704</td>
</tr>
</tbody>
</table>

Note: *** p<0.05, ** p<0.1, * p<0.15

The results from Model 1-4’s are presented in Table 6.3. Removing the electricity prices variable from the base analysis in Model 1 resulted in decreasing the adjusted R² from 0.736 to 0.709. Taking out the variable of urban roads and incentive in Model 2 and Model 3 reduced the adjusted R² to 0.725 and 0.733, respectively. Considering the results of the sensitivity analysis, it is possible to conclude that the significance order of electricity prices, urban roads, and incentives is declining. Despite, the significant effect of these three factors on EV shares, eliminating of these factors does not decrease the
explanatory power significantly (adjusted $R^2$ equal to 0.704). This shows that states specific fixed effects explain the most part of EVs share variation. Thus, in order to analyze the sensitivity of different states’ EV shares with respect to electricity price, urban roads, and incentives, the variation of state specific fixed effect on models 1-3 was analyzed.

Table 6.4 States’ sensitivity analysis results

<table>
<thead>
<tr>
<th>Base Model</th>
<th>Model 1 (electricity prices)</th>
<th>Model 2 (Urban roads)</th>
<th>Model 3 (Incentives)</th>
<th>Model 4 (all three)</th>
</tr>
</thead>
<tbody>
<tr>
<td>State</td>
<td>Fixed factor change</td>
<td>State</td>
<td>Fixed factor change</td>
<td>State</td>
</tr>
<tr>
<td>NJ</td>
<td>-6.09</td>
<td>VT</td>
<td>-2.60</td>
<td>NJ</td>
</tr>
<tr>
<td>VT</td>
<td>5.34</td>
<td>AK</td>
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<td>MA</td>
</tr>
<tr>
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<td>-4.54</td>
<td>NY</td>
<td>-1.61</td>
<td>FL</td>
</tr>
<tr>
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<td>-3.11</td>
<td>AL</td>
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<td>CA</td>
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<tr>
<td>IL</td>
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<td>MI</td>
<td>-0.75</td>
<td>AZ</td>
</tr>
<tr>
<td>OH</td>
<td>-2.21</td>
<td>OK</td>
<td>-0.68</td>
<td>NY</td>
</tr>
<tr>
<td>AK</td>
<td>1.89</td>
<td>CA</td>
<td>-0.60</td>
<td>OH</td>
</tr>
<tr>
<td>NY</td>
<td>1.84</td>
<td>NC</td>
<td>-0.55</td>
<td>GA</td>
</tr>
<tr>
<td>OR</td>
<td>1.34</td>
<td>OH</td>
<td>-0.42</td>
<td>NC</td>
</tr>
<tr>
<td>OK</td>
<td>-1.33</td>
<td>OR</td>
<td>-0.29</td>
<td>MI</td>
</tr>
<tr>
<td>TN</td>
<td>-1.30</td>
<td>TN</td>
<td>-0.24</td>
<td>IL</td>
</tr>
<tr>
<td>AZ</td>
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<td>AZ</td>
<td>-0.13</td>
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<tr>
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<td>CO</td>
<td>-0.04</td>
<td>AL</td>
</tr>
<tr>
<td>NC</td>
<td>-0.92</td>
<td>GA</td>
<td>-0.03</td>
<td>CO</td>
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<tr>
<td>MI</td>
<td>0.70</td>
<td>IL</td>
<td>0.06</td>
<td>OR</td>
</tr>
<tr>
<td>CA</td>
<td>0.60</td>
<td>MA</td>
<td>0.15</td>
<td>OK</td>
</tr>
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<td>FL</td>
<td>0.53</td>
<td>AK</td>
</tr>
<tr>
<td>GA</td>
<td>-0.18</td>
<td>NJ</td>
<td>0.91</td>
<td>VT</td>
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</tbody>
</table>

The coefficients of developed base model are based on the various U.S. states data over time. However, impact of various explanatory variables on each individual state is unknown. In order to analyze the sensitivity of each state EV share with respect to electricity prices, urban roads, and incentives, the effect of removing one of the explanatory variables on states’ fixed effect factor were investigated. When a variable
remove from the model, it is considered as unobservable variable, which influence the model through the fixed effect. When the removed variable has positive correlation with state EV share, state’ fixed effect factor increases, and vise versa. Table 6.4 describes the order of states’ sensitivity with respect to proposed explanatory variables.

According to the base model results, it is expected that electricity price be a deterrent factor, which reduces the utility of EVs. The negative value in column associated with electricity price in Table 6.4 (Model 1) demonstrates discouraging impact of electricity price in various states. State of Vermont is most sensitive state with respect to electricity prices. This effect is decreasing over states in order in such a way that state of Georgia sensitivity with respect to electricity price is lowest and the encouragement impact of this factor on EV adoption is negligible. However, the results imply that the electricity price does not have negative effect on EV adoption rate in the states of Illinois, Massachusetts, Florida, and New Jersey. Therefore, except the states of Illinois, Massachusetts, Florida and New Jersey, decreasing the electricity price is a policy to increase the EVs utility, which has different effectiveness in various states. Regarding the urban roads variable, it could be concluded that the sensitivity of EV share with respect to this variable in New Jersey is the most, and in Arkansas is the least. This conclusion is based on the increasing the fixed effect factor in various states resulted by removing urban roads variable. In contrast, urban roads variable does not have positive effect on state of Vermont EV share. Comparison of states fixed effect of base model with Model 3 (incentive variable excluded model) revealed that the encouragement impact of incentives on EV adoption rate in New Jersey and Oregon States are highest and lowest,
respectively. Providing incentives does not have any positive effect on stimulating consumer to adopt EV in the states of Arkansas and Vermont.

Summary and Discussion

Demand for travel has been persistently increasing for several decades as a result of population and economic growth (Heaslip et al. 2014). However, at the same time, emissions from transportation sector have contributed to a large share of air pollution and caused significant concerns regarding air quality and public health. Moreover, oil consumption surge during past decade has increased the U.S. dependency on foreign oil. In order to address concerns regarding air quality and oil dependency, increasing the use of electric vehicles as green vehicle is helpful. Hence, the motivation of this study is to draw connection among EVs share, government incentives, and different socioeconomic factors.

In this research, a macroscopic binomial logit market share model was conducted to investigate transportation modal choice between EV and conventional vehicles. In proposed model, the mode choice decision was assumed to be a function of income, vehicle miles traveled, gasoline price, electricity price, urban roads, presents of incentive, and HOV lane privilege. The model was estimated using different panel data methods over data for 19 U.S. states from 2003 to 2011.

Results demonstrated that electricity prices, urban roads, and incentives are effective factors on commuters’ mode choice decision. Decreasing electricity price increases the EVs share, while increasing urban roads and incentives increase utility and
share of EVs. Considering sensitivity analysis, electricity price is most influential among these three factors. In addition, sensitivity analysis of different states EVs share with respect to these three factors expressed that Vermont State has highest sensitivity of electricity price, and New Jersey is most sensitive state with respect to urban roads and incentives. Considering results of different states sensitivity analysis, different policies can be implemented associated to each state. For instance, decreasing the electricity price could be suggested to increase the share of EVs in Vermont State. In New Jersey State expanding urban roads and offering more incentives are most influential on EVs share increment.

Moreover, this study investigated the effect of different time points and time trend on EV share. Lower EVs share at 2005, 2006 was due to Hurricane Katrina, and at 2008 as result of economic recession. After these phenomena commuters roughly chose EVs due to the disrupted socio and economic conditions. Time trend model’s result demonstrated that the passing time has been increasing the EVs share. It is based on the effect of time on new technology diffusion. Over time people knowledge about new technology has been increasing, and it makes their mind ready to accept new technology.

Incentive variable in this study were considered as dummy variable, since most of the incentives over states are estimated based on the vehicle price, which is unavailable data over time. In order to have more accurate results, it is suggested to accomplish the modeling on data with monetary incentive values. At the time of this research the vehicle price data of 2010, 2011, and 2012 were available. But the data related to number of EVs at 2012 was not available. Finding number of EVs data of 2012, the EV share model with
monetary values of incentives can be estimated over different states for time points 2010, 2011, and 2012.

Another suggestion for future work can be providing data related to EVs’ infrastructure. This is an issue that can be incorporated into the model as well. For instance, construction of more charging station will increase the EV’s range, which increase EVs utility and encourage commuters to adopt EVs.

References


CHAPTER 7

CONCLUSION

Increasing demand and consumption of motor fuel raised a concern regarding energy security along with the unstable international oil prices. Therefore, many policies are being considered to reduce transportation fuel consumption not only to enhance the country's energy dependency but also to help reduce greenhouse-gas emissions, and improve air quality. This research examined the impacts of transportation energy policies on key transportation parameters. The quantitative approach specifically the econometric models were used to analyze various policies considered in this study.

In Chapter 1, a brief introduction of the research background and an outline of the dissertation are given. Chapter 2 is a comprehensive literature review and considers different approaches of this research.

The potential rate of natural gas vehicle adoption was examined and discussed in chapter 3. A framework was developed to model CNG vehicle adoption rate considering two different approaches; adoption of CNG cars as single vehicle by consumers located inside the CNG vehicle’s leisure trip range, and adoption of CNG vehicles as a second car for consumers outside of that range. The results showed that the proportion of commuters, which are interested in adopting CNG cars, is highly dependent on the distance of travel (VMT), natural gas and gasoline price deferential, and CNG and conventional vehicles price differential. These results demonstrate that the consumers located farther from their work are more likely to adopt a CNG vehicle even when the vehicle price differential is large and the fuel price differential is small. These consumers
can still recover the high purchase price differential with savings on fuel costs. In situations that VMT is low, the fuel and vehicle price differential are more influential. The high fuel price differential and low vehicle price differential increase the willingness of people to adopt CNG cars. The results indicate that the proportion of the vehicle fleet that would find a CNG fuel system economically advantageous is small. This prediction reflects the current share market. Simulations suggest that a substantial decrease in the vehicle price differential for CNG vehicles is necessary to induce CNG vehicle adoption for a significant portion of the vehicle fleet. Moreover, the model predicts that even with technology improvements that allow for lower conversion costs or lower manufacturer vehicle price differentials, CNG vehicles are likely to remain a minority in the vehicle fleet.

The model predicts that overall CNG vehicle adoption rate will be low. However, higher CNG vehicles single trip range, morefuel infrastructures, and lower production costs due to technology improvements, are some of the factors that lead to higher CNG vehicle adoption rate.

Changes in the vehicle fleet composition and driving habits can affect this analysis. For instance, if consumers respond to gasoline price increment by driving less and purchasing more fuel-efficient vehicles, the potential gains from CNG vehicle adoption will be diminished. To summarize, the model suggests that CNG is most likely to be cost-effective for the following conditions: high travel millage; low MPG vehicles; high gasoline price relative to natural gas; and existence of adequate fuel infrastructures.
Chapter 4 addresses how higher usage of natural gas vehicles affects travel demand. Natural gas vehicles may induce more trips, due to lower fuel price. In order to analyze the impact of natural gas vehicles on travel demand, accurately estimating the price elasticity of travel demand is essential. The developed model is based on time series data of Washington State. In addition to the VMT model, another model was adapted to exclude population effects. VMT and VMT per capita were forecasted in multiple scenarios by assuming the natural gas price and the associated adoption rate. The results specified that due to the low fuel price elasticity of aggregated automobile use (both VMT and VMT per capita) induced travel by NGVs will not be considerable. In addition, the results of models and data analysis demonstrated that considerable amount of VMT growth is due to population. Gasoline price increment is another policy that controls VMT. In VMT Model, the negative effect of gasoline price increment on VMT is defined through the coefficient of fuel price. On the other hand, higher gasoline price results in higher usage of NGVs, which slightly induces VMT. However, due to the negligible share of NGVs the consequence of this effect is not considerable. Higher fuel price coefficient value in VMT per capita model compared to VMT model, explains the higher impact of fuel price on VMT when population is under control.

In the chapter 5, the impacts of fuel efficiency improvement on fuel tax revenue and GHG emissions are examined. The study estimated the elasticities of fuel consumption with respect to fuel efficiency and fuel price and also the rebound effect. The VMT and MPG models were developed as a system of equations to take into account the simultaneous effect of VMT and MPG on each other. The model estimation was
based on the annual time series data for Washington State. The Model was considered as a system of equations to have both VMT and MPG as endogenous variables. While MPG acts as an exogenous variable in VMT equation through fuel cost per mile variable, it is under influence of fuel price and VMT in MPG equation. The VMT was considered in MPG equation because it is expected that commuters who drive more try to increase the fuel efficiency more than other commuters.

Fuel consumption analysis showed the relative importance of different exogenous variables. However, higher fuel efficiency and gasoline price are two effective factors reducing fuel consumption, the number of registered vehicles (representative of population) and employment (representative of economic activities) are more influential. Therefore, besides improving fuel efficiency, implementing policies controlling number of registered vehicles and trips would be beneficial. Accordingly, travel demand management (TDM) strategies can help people use the transportation system more efficiently, while reducing fuel consumption and vehicles GHG emissions. These strategies include activities such as: eliminating or shortening trips; changing the travel mode; as well as increase of carpooling, vanpooling, transit, bicycling and walking.

Moreover, it was demonstrated that estimated fuel efficiency would be the cause of 106 million dollars loss in fuel tax revenue of Washington State in 2031. As a result of fuel efficiency improvement, $CO_2$ produced from fuel burning decreases by 8.7% in 2031.

The motivation of chapter 6 is to draw connection among EVs share, government incentives, and different socio-economic factors. In this research, a macroscopic binomial
logit market share model was developed to investigate transportation modal choice between EV and conventional vehicles. In proposed model, the mode choice decision was assumed to be a function of income, vehicle miles traveled, gasoline price, electricity price, urban roads, incentive, and HOV lane privilege. The model was estimated using different panel data methods over data gathered for 19 U.S. states from 2003 to 2011. Results demonstrated that electricity prices, urban roads, and incentives are effective factors on commuters’ mode choice decision. Decreasing electricity price increases the EVs share, while increasing urban roads and incentives increase utility and share of EVs. Considering sensitivity analysis, electricity price is most influential among these three factors. In addition, sensitivity analysis of different states EVs share with respect to these three factors expressed that Vermont State has highest sensitivity of electricity price, and New Jersey is the most sensitive state with respect to urban roads and incentives. Moreover, this study investigated the effect of different time points and time trends on EV share. Hurricane Katrina in 2005 and 2006, and economic recession in 2008 resulted in lower EVs share. After these phenomena, commuters roughly chose EVs due to the disrupted socio and economic conditions. Time trend model’s result demonstrated that EVs share has increased over time due to the positive effect of time on new technology diffusion. In this study, incentives were considered as a dummy variable, because most of the incentives are based on the vehicle price, which is unavailable data over time. In order to have more accurate results, it is suggested to accomplish the modeling on data with monetary incentive values. Another suggestion for future work is incorporating the number of EVs’ infrastructures in model development. Construction of more charging
stations will increase the EV’s range, which will increase utility of EVs and will encourage commuters to adopt EVs