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Predicting passenger trips for future energy and transportation investment planning

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Predicting passenger trips for future energy and transportation infrastructure investment planning

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ABSTRACT

Passenger Transportation is one of the two major components of transportation sector (the other being freight) and it is one of the major factors affecting the energy demand and the need for transportation infrastructure investments. Specifically, 12% of energy consumption and almost 17% of total greenhouse gas emissions in the United States are attributed to passenger transportation, while the energy consumption due to passenger transportation is almost 60% of the total energy consumption in transportation sector. These statistics indicate the importance of predicting passenger transportation for future energy and transportation infrastructure investment planning. Vehicle Miles Traveled (VMT) is one of the most common measure estimating passenger trips in the United States and has been traditionally used to determine the need for new infrastructure. As the availability of energy resources and the funding for new infrastructure decrease, the need of forecasting VMT in the future for energy and transportation investment planning becomes vital.

Various studies in the past have determined the factors affecting VMT. Demographic and socioeconomic characteristics, road infrastructure, and land use influence the amount of passenger trips, but also fuel prices and government policy. Increase of population and income per capita has been traditionally the factor resulting directly to the increase of VMT while areas with higher density result to lower per capita single vehicle travel demand. Moreover, the increase of fuel cost decreases VMT while the impact of lane miles is totally opposite.

While previous studies have investigated the effect of demographic and socioeconomic characteristics, or the effect of land use and road capacity, or the effect of fuel prices on VMT, the effect of these factors has not been fully examined in a multivariate context. The objective of this thesis is to determine the factors that influence passenger trips and develop a prediction model of VMT in the future. Using panel data for the 48 continental states during the period 1998-2008, simultaneous equation models were developed for predicting VMT on different road functional classes and examining how new technology (telecommuting, alternative fuel vehicles) but also changes in fuel prices can affect the amount of passenger trips across the nation. Moreover, a panel data regression model with random coefficients was developed to identify the factors affecting total VMT. The use of panel data allows for the determination of the influence of different factors but also the effect of these factors across different states and years. To assess the influence of each significant factor on VMT, elasticities were estimated.

Further, the effect of innovations in technology (such as telecommuting and alternative fuel vehicles) and various government policies on energy consumption and greenhouse emissions was investigated. Different scenarios for high speed rail network, alternative fuel vehicle market share, fuel tax and density in the future were developed in order to quantify that impact. The estimation results of the model for total VMT were used to estimate the influence of each policy and scenario on the amount of total VMT, while the reduction of energy consumption and greenhouse gas emissions was estimated using the software VISION, developed by the Argonne National Laboratory.

The estimated models of passenger trips can assist transportation planners and policy-makers to determine the energy and transportation infrastructure investment needs in the future.

Key words: Passenger trips, energy consumption, infrastructure plan, policy, new technology.

CHAPTER 1 INTRODUCTION

1.1 Purpose of this study

The purpose of this study is to forecast passenger trips by automobiles in United States (U.S.) and determine the energy demand in the future. Vehicle Miles Traveled (VMT), a common measure of passenger trips in the United States, has been traditionally used to determine the need for new infrastructure. Using panel data for the 48 continental states during the period 1998-2008, simultaneous equation models are estimated for predicting VMT on different road functional classes as a function of demographic and socioeconomic characteristics, land use, fuel cost and length of highway network. This study also examines how different policies and changes in fuel prices can affect passenger trips across the nation. Moreover, the author investigates how innovations in technology will affect energy consumption and greenhouse emissions, through different scenarios for alternative fuel vehicle market share, expansion of the passenger rail network, increase of density and increase of trip cost (fuel cost and fuel taxes) in the future.

The data for this study was collected from different agencies in the U.S. The Federal Highway Administration (FHWA), the CENSUS 1990, 2000 and projections for 2008, the Highway Performance Monitoring System (HPMS), and the Highway Statistics provided information on passenger trips, demographic and socioeconomic factors, highway network, land use, and fuel cost for the continental states from 1998-2008. Moreover, data for alternative fuel vehicles was provided from the U.S Department of Energy and the Energy Information Administration. Appropriate methodology was developed and software application was involved in determining the energy demand in the future.

1.2 Importance of prediction of VMT and energy demand

Passenger Transportation consists of one of the two major components of transportation sector (the other being freight) and it is one of the major factors affecting the energy demand and the need for transportation infrastructure investments. Passenger transportation consists of 12% of energy consumption and almost 17% of total greenhouse gas emissions in the United States, while the energy consumption due to passenger transportation is almost 60% of the total energy consumption in transportation sector. As energy and availability of energy resources have become major global challenges, the prediction of future energy needs and the reduction of energy consumption are of increasing importance.

Vehicle Miles Traveled (VMT), a common measure of passenger trips in the United States, has been traditionally used to determine the need for new infrastructure. Adding new capacity is expensive and investment planning is necessary in order to ensure the most efficient allocation of limited resources. Moreover, determining the various factors affecting VMT can assist transportation engineers to estimate the influence of various policies in the future. For example, the extension of passenger railroad or the increase of fuel taxes would affect directly passenger trips and as a result, the infrastructure needs and energy consumption in the future.

1.3 Contribution of this study

The influence of various factors on VMT has been investigated extensively in past studies. Previous studies have already indicated the effect of demographic and socioeconomic factors, highway network, land use and fuel cost on VMT. Increase in population and income has contributed to the increase of passenger trips in the past, and the effect of gender and race has been examined in past studies as well. Moreover, the size of household but also the education and the number of children have been found to affect VMT. Factors such as the fuel or the trip cost, the number of vehicles, the land use and the length of the network also have been examined in previous studies. The effect of fuel cost is the most ambiguous one and the results are not so consistent among the various studies. On the other side, the influence of land use has been extensively analyzed and various types of developments, such as mixed or separate uses, have been examined in order to determine the effect on VMT. Moreover, the length of the network affects VMT and its increase of results to increased number of trips. Last, the increased amount of vehicles has contributed to an increase of passenger trips.

While previous studies have investigated the effect of demographic and socioeconomic characteristics, or the effect of land use and road capacity, or the effect of fuel prices on VMT, the effect of these factors has not been fully examined in a multivariate context. Moreover, this study examines the influence of new technology, such as alternative fuel vehicles or telecommuting, on VMT and passenger trips. Finally, the estimated VMT models are used to determine the energy consumption and the greenhouse gas emissions in the future according to various scenarios for alternative fuel vehicle market share, expansion of the passenger rail network, increase of density and increase of trip cost (fuel cost and fuel taxes) in the future.

However, these effects (and corresponding magnitude) have changed over the years and different significant factors are identified to determine VMT, according to the time of the study and the place.

1.4 Structure of thesis

The structure of this study is the following:

The **second chapter** presents the literature review. Previous studies that have examined VMT and have determined the factors affecting VMT are cited and the major results of these studies are summarized. The studies are presented according to the factors that they have examined and the place of analysis (local, regional, or country). A table summarizing the studies and their results is included at the end of the chapter.

The **third chapter** describes the data. A table with descriptive statistics of the variables used in the analysis is included. Moreover, various figures are presented that visualize the data and provide the main trends of the variables during the study period 1998-2008.

The **fourth chapter** presents the methodology that was applied to predict VMT in the future. In addition, the estimation results of VMT are presented by functional class and type of area.

The **fifth chapter** examines energy demand in the future. Different scenarios are developed and their influence on energy consumption and greenhouse gas emissions in the future is examined.

The **sixth chapter** consists of the conclusions and the recommendations. The major conclusions of this study are discussed but also the limitations of it. Last, recommendations for future research are offered.

CHAPTER 2 LITERATURE REVIEW

2.1 Overview

As indicated in Chapter 1, the aim of this thesis is to determine the factors that influence the amount of Vehicles Miles Traveled (VMT) in USA. VMT is a measure of highway travel, and can show changes in travel behavior across different time periods. In addition, VMT can indicate the need for new investments on highway infrastructure. A number of studies have focused on VMT, VMT growth rates and the factors that influence VMT. This chapter provides a review of previous studies on this topic, with an emphasis on the factors that affect VMT such as demographic and socioeconomic factors as well as land use, fuel prices and government policies.

2.2 Previous Studies

2.2.1 VMT and demographic and socioeconomic factors, land use and fuel prices

2.2.1.1 Studies at the National level

Greene et al (1995) developed a nationwide model to investigate the relationship among fuel prices, income and VMT. The model included the following variables: income, cost per mile, fuel price, value of time spent on highway, average speed, population, age and gender. It was found that an increase in the income contributes to an increase in VMT while an increase in fuel prices decreases VMT, as anticipated. The authors also indicated that population is the most predictable variable in order to project the amount of VMT in the future years.

Litman (2005) associated the amount of VMT with demographic and socioeconomic characteristics, and land use and vehicle operating costs. According to this study, as the baby boom generation retires, total VMT will decrease. Moreover, race and origin affect travel patterns and should be included in determining VMT. It was also indicated that income affects vehicle ownership; vehicle ownership increases twice as fast as per capita income. The author argued that rising energy prices would probably cause only modest mileage reductions in the future. As vehicles become more fuel efficient, fuel prices do not influence trips as much as it might be expected. Likewise, fuel taxes do not contribute to significant changes in VMT, as they consist of only half of fuel prices or less. Furthermore, land use was found to have a significant effect on travel patterns. Residents and employees who live in more accessible locations, with more alternative transportation modes available, tend to own fewer vehicles, and drive less, compared to people who live in less accessible and more dependent to automobile regions.

The Committee for the Study on the Relationships among Development Patterns, Vehicle Miles Traveled, and Energy Consumption (2009) examined the relationship between VMT and land use. According to that report, a more compact development with higher densities for both, the place of residence and employment leads to reduction of VMT, and decrease in energy use and emissions. In the same report the effect of high energy prices on VMT was examined but also, the case of increasing fuel taxes in order to reduce greenhouse emissions. According to the authors, people tend to respond to fuel price increases in the short-run by reducing their trips and in the long term by purchasing more fuel-efficient vehicles. However, the long-term effect of changes in fuel prices and taxes is different, as it contributes to relocation of houses or business to more dense areas in order to reduce both the frequency and the distance of trips. After analyzing the VMT in 32 cities in the United States and abroad, Newman and Kenworthy (1999) concluded that gasoline consumption is higher in US cities than abroad due to the lower metropolitan density in US cities. Krizek (2003) estimated that the VMT decrease by about 5 VMT per day per household in neighborhoods with higher accessibility, while the influence of fuel cost on VMT is much lower. The Congressional Budget Office (CBO, 2008) found a change in travel behavior due to high gasoline prices ($4 per gallon) experienced during the last years. The short-run elasticity for fuel price was estimated around -0.006 while the long-run elasticity was estimated a bit lower, around -0.04. Last, regarding gasoline taxes, CBO indicated that the gasoline taxes would have to be very high in order to influence travel behavior in the US, as gasoline taxes are a very small percentage of total fuel prices.

The National Surface Transportation Policy and Revenue Study Commission (2007a) studied trends of VMT and travel demand according to population and income. The growth of passenger travel is much higher than the growing rate of population and almost equal to the growth rate of personal income. However, since 2000, the growth rate for VMT has slowed down while the rate for personal income has continued to increase. Personal income influences travel demand (amount of trips by car, length of trips) but also the expected quality of transportation system. People with higher income tend to own more cars, travel more and longer distances for work but also for social/ recreational activities, while people of lower income make fewer and shorter trips. However, the influence of income on travel demand in the future is projected not to be as significant as the growing rate of VMT is slowing down.

Polzin (2006) estimated that vehicle availability would reach a saturation point in the future and so the impact of vehicle availability on VMT will not be as high as in the past. The number and length of trips would remain stable, due mainly to the expected increase in the cost of travel. The growing rate of number of trips per person and trip length in the future is projected to be equal to one per third of the growth rate in the past. At the same time, the author estimated the overall annual growth of VMT around 2%.

Puentes and Tomer (2008) also indicated that VMT began to plateau at 2004 and dropped in 2007. While the total amount of VMT in rural and urban roads increased between 1997 and 2008, the amount of VMT in rural and urban roads has been decreased from 2004 to 2007. Moreover, the authors examined the rates of VMT in different regions. Southeastern and Intermountain West states had higher growth rates for VMT between 1991 and 2006, while the rates for the Great Lakes, Northeastern and Pacific states are smaller. Furthermore, the authors indicated that the greatest VMT per person occurs in low density Southeastern and Southwestern metropolitan areas.

The significant but smaller effect of income on VMT is also indicated by National Surface Transportation Policy and Revenue Study Commission (2007b). Income influences the amount of trips, but over time the most important factor affecting travel demand is population and its projected growth. Other demographic characteristics that influence travel demand are the age and the gender. Also, the regional migration and the urban development seem to have a significant role on the projection of VMT. The suburbanization is directly connected with the increase in use of automobile, increasing at the same time the number of

VMT while more densely populated areas and areas with mixed uses contribute to the decrease of trips by car.

Burchell et al. (2002) developed a regression model in order to predict the personal miles of travel as a function of income, gender, household size and type of development, using data from the 1995 National Personal Transportation Survey. According to their model, shifting of residences and jobs from sprawl to the controlled-growth scenario would reduce person miles by about 4%, corroborating previous research that more compact development results in a decrease in VMT.

Southworth (2001) also analyzed the effect of urban sprawl on VMT. This type of development, the socio-economic and demographic growth and the decrease in the cost of travel during the past decades contributed to an outstanding growth of VMT. The spatial pattern, the intensity and the mix of land use were found to affect VMT. More specifically, separated land uses results in the increase of length but also frequency of trips with a direct effect on the total amount of VMT, while higher density and mixed land use contribute to a decrease in trips. Turning to the price elasticity of demand, which represents the effect of the cost of travel on VMT, the author noted that the cost of travel in the US has decreased since 1970, a fact that results in an increase in trips, as expected. Furthermore, Southworth mentioned that the extension of the highway system has also contributed to longer trips. However, the author noted that the increasing rate of VMT in the future will be lower, compared to the past.

Barr (2000), using data from 1995 National Personal Travel Survey, estimated the relationship between VMT and travel time, taking into account demographic, socioeconomic and land use characteristics. The following equation was developed and fifteen models were estimated:

$$\text{Log}(VMT_i)=\alpha+\sum\beta_k \log(X_i)+\varepsilon_i \qquad \textbf{(2.1)}$$

The travel time elasticity was estimated to range between (-0.350) and (-0.582) and the negative sign indicates that a decrease in travel time results in an increase of VMT. Adding highway capacity increases travel demand by 3-4% while an increase of income by 10% results in an increase of VMT by 3-4 % also. Moreover, each additional family member in a household increases the annual household VMT by 5-25% while the effect of an additional worker in the family is higher, as each additional worker increases the annual VMT by 20-33%. Last, the population density is significant and in case that the population density of an area is doubled, the decrease in VMT per capita is around 4-6%.

The National Energy Modeling System (2001), used fuel prices, personal income and population projections in order to forecast the amount of VMT. According to the developed model, the aging population and the increasing ratio of female drivers to male drivers would be the main factors that influence VMT per driver in the future. The model was developed in two stages: at the first stage, the model forecasts the VMT per driver, based on historical data, assuming that the age profile of the country remains constant. During that step the following equation was developed:

$$VMTPD_T=\rho VMTPD_{T-1}+3.593\,(1-\rho)-0.088(CPM96_T-\rho\, CPM96_{T-1})+1.64*10^{-4}\,(YPC96_T-\rho\, YPC96_{T-1})+6.632(PrFem_T-\rho PrFem_{T-1}) \qquad \textbf{(2.2)}$$

where

VMTPD = the vehicle miles traveled per driver

CPM96 = the fuel cost of driving a mile, expressed in 1996 dollars

YPC96 = the disposable personal income per capita, expressed in 1996 dollars

PrFem = the ratio of per capita female driving to per capita male driving

ρ = the lag factor, estimated using the Cochrane-Orcutt iterative procedure to be 0.758

T= current year

T-1= previous year

According to Equation (2.1), an increase in the per capita income and of the ratio of per capita female drivers to per capita male drivers would result in an increase in VMT per driver, while the increase of fuel cost would result in decrease in VMT per driver.

Mabe (2007) developed the following equation in order to estimate the influence of gas prices on travel demand:

$$Qdrive = aInc^{\beta inc} * Psub^{\beta Psub} / Pdrive^{\beta Pdrive} \quad \textbf{(2.3)}$$

where

Qdrive: demand for driving

Inc: Personal income

P: price of its good (driving, substitute)

βi= elasticity of i (driving, substitute)

a= constant

The income elasticity was estimated equal to +1.16, while the price elasticity for gasoline was equal to -0.06 and the price elasticity for airfare (substitute) was equal to +0.13. The author concluded that increases in income and airfare increase the demand for driving while increases in gas prices have the opposite effect.

Liddle (2009) examined the effect of different factors on VMT using data from 1936-2004. According to this study, the travel demand increased with the income while the increases in fuel prices resulted in decreases in fuel consumption. Moreover, the author argued that while the gasoline cost influences the decision about the type of vehicle to purchase, the gasoline prices were statistically significant only in the long run.

Kweon and Kockelman (2004) used the 1995 National Personal Transportation Survey in order to determine the effect of household income, vehicle ownership, number of workers, housing location (urban/rural), retirement, public transit availability and housing type on household VMT for different levels of density. The authors corroborated previous findings that the annual household VMT increases as density decreases but also found that the amount of VMT per household can be higher in high density areas with no public transit available, and can be lower for households who own a house in high density areas. Moreover, higher density in urban areas resulted in lower VMT compared to higher density in rural areas. Turning to the number of workers and number of vehicles, an increase in the number of workers or vehicles per household would result in an increase of the annual VMT per household. Last, annual VMT per household would increase as household income increases.

McGuckin and Liss (2005) presented some interesting findings from the 2001 National Household Travel Survey (NHTS). Although the number of daily trips per person in 2001 was almost the same with the number of daily trips per person in 1995, the average distance of daily trips has increased and resulted in an increase of VMT. An important factor associated with the VMT increase was the increase in household vehicles, which almost doubled during the last 25 years, and so the income levels.

Hu et al. (2000) used data from the 1977, 1983, 1990 and 1995 National Household Travel Surveys in order to estimate the average vehicle miles traveled per driver. The authors developed a regression model in order to determine the VMT). The developed model is described by the following equation is:

$$\log(\text{VMT}) = \text{constant} + \alpha_1 \log(\text{income}) + \alpha_2(\text{fuel price}) + \alpha_3(\text{health status}) + \alpha_4(\text{employment status}) + \alpha_5(\text{other drivers available in household}) + \alpha_6(\text{year}) \quad \textbf{(2.4)}$$

The coefficients for the variables in the model were estimated as:

α_1=0.305

α_2=-1.5-(-2.2)

α_3=0.0868

α_4=0.4991

α_5=-0.1279

α_6= 0.0218

So, higher income, better health and being part of the workforce would increase VMT per driver, while the increase in fuel prices and the higher number of drivers in household would decrease VMT per driver. The variable for the health is based on the ALS ranking from NHIS. Moreover, the authors estimated that every year the amount of VMT per driver increases too.. Another interesting result was the estimation of elasticity for older men and women. The elasticity for old men was equal to 0.80 while the elasticity for old women was equal to -0.69.

Polzin et al. (2004) used data from the 2001 NHTS and developed two different equations for predicting VMT in the future. The first equation-model is described as follows:

Vehicle miles=population*(person trips/persons)*(person miles/person trips)*(vehicle miles/person miles) **(2.5)**

According to the authors, the population consists of a significant but not the dominant factor for VMT growth, result that is interesting since the rest of the studies consider population as the dominant factor for VMT growth. The most important factors contributing to the increase of VMT were the increase in trip rates (49% increase for the time period 1977-2001), and the increase in the average trip length (10% increase due to the suburbanization of most of cities).

The second equation-model developed in the study was:

Vehicle miles= population*(person hours/persons)*(vehicle miles/person hours) **(2.6)**

The contribution of population in the increase of VMT was exactly the same with the first model. The person travel time has increased by 1.8 min per year contributing to the increase of VMT. The authors noted that there has not been a constant trend of the vehicle miles per hour; there was an increase in 1995, but a decrease since then.

Souleyrette et al. (1995) supported that the amount of VMT can be estimated by population, the length of trips and number of vehicles using the following equation:

VMT= [(number of vehicles)/population]*population*[(trips (miles))/vehicles] **(2.7)**

The number of vehicles depends on the market penetration and the driving-age population. The authors concluded that the increases in VMT in the future would be driven from increases in population and increases in the number of vehicles.

2.2.1.2 Studies on specific areas

Heanue (1997) examined the effect of demographic, socioeconomic and land use factors on VMT growth. Using the city of Milwaukee, Wisconsin as a case study the author compared the travel growth over time due to these factors with the travel growth generated or induced by new highway capacity. The results showed that, during 1963-1991, the percentage of VMT growth due to the expansion of highway capacity was between 6-22%, while the increase of VMT caused by socioeconomic or other factors was much higher, around 78%.

Brazil and Purvis (2009) developed a GIS-based tool, the BASSTEGG, for calculating the automobile availability, the vehicle usage, the fuel usage and the greenhouse emissions by each household in San Francisco Bay Area. According to their study, the amount of VMT is higher in rural areas compared to urbanized areas. Moreover, as it was expected, households with higher income have greater number of VMT compared to households with lower income, in the same area. Also, as number of workers and number of vehicles increase, VMT per household would increase too.

Stone et al. (2005) used data from the 1995 National Personal Transportation Survey, the Freight Analysis Framework, Census 1990 and 2000, and data for residential and commercial traffic for Minnesota, Wisconsin and Michigan in order to determine factors that influence VMT. The results showed that VMT are higher within urban areas but also concentrated along major interstate corridors. In rural areas, the VMT/ km^2 are lower compared to urban areas, probably due to the smaller number of households per block group.

2.2.2 VMT and land use

Cervero and Duncan (2004) used travel-diary data for San Francisco Bay Area from the 2000 Bay Area Travel Survey (BATS) and examined the effect of various types of mixed land use on vehicle travel. There were positive correlations between accessibility, number of trips and trip links. However, although places with higher accessibility attract more people and subsequently more trips, people who live in more accessible areas do shorter trips or use the transit system. The authors concluded that high accessibility and mixed-use growth increases the total amount of trips but decreases their length and the travel time.

Brownstone and Golob (2009) used data from National Household Travel Survey 2001 and examined the impact of residential density on both vehicle usage and energy consumption. A simultaneous equation model with 3 endogenous variables (total annual household miles, total annual household fuel usage and housing units per square mile) was developed in order to estimate the effect of land use on fuel consumption. The study found a great effect of land use on travel behavior: households located in denser areas tend to drive 1,171 miles per year less than households in less dense areas. More specific, a lower density of 1,000 housing units per square mile leads to an increase of 4.8% of annual miles driven and an increase of 5.5% on fuel usage. Moreover, the number of drivers per household influences the household annual mileage, and the fuel usage through the mileage but also through residential density. Regarding income, the authors found that the relationship between the income and the fuel usage is linear. Moreover, the number of children and the education also affect the fuel usage, but also life-cycle and race. The authors concluded that among the exogenous variables, the number of drivers and the number of workers have the greater impact on fuel usage.

Chatman (2008) used data from a phone survey in San Francisco and San Diego and indicated that the correlation of residential density with the frequency of automobile trips is negative for non-work activities. In fact, each marginal increase of one thousand residents per road mile results to a 63% reduction in the number of the auto-accessed non-work activities. Moreover, the author concluded that for each additional 100 residents and employees per developed acre, a reduction of 47% in the number of the non-work automobile trips is observed.

Boarnet and Crane (2001), using data for San Diego, examined the influence of land use on travel behavior. The households living further from the central business district tend to make, as expected, more non-work car trips, but the effect reverses signs at a distance of approximately 25 miles from downtown. Moreover, the land use variables had an impact on trip prices; impact that affects also the amount of trips. Furthermore, the authors noted that the non-work car trips and the frequency increase as income increases. The interesting result is that the trip frequency increases with income up to a specific level and then decreases.

Ewing et al. (2007) developed an estimation of the reduction of CO_2 due to a greater compact development. The VMT per capita, in case of compact development, is 30% less compared to conventional developments. That development would reduce the total transportation related CO_2 emissions from current trends by 7-10% in 2050 . However, the compact development will affect only the amount of VMT in urban areas and not in rural areas.

Bagley and Mokhtarian (2002) examined the impact of residential neighborhood type on travel demand behavior, using data collected in 1993 for five neighborhoods in San Francisco Bay Area. The number of vehicles is positively related to VMT while also the gender affects the travel demand. Moreover, the lifestyle and attitudinal characteristics seem to have the greatest impact on travel behavior. Adventure-prone people, pro-driving, not favoring transportation alternatives or not being time-sensitive tend to travel more with personal vehicle. The effect of residential location on VMT is much smaller. The authors concluded that lifestyle and attitudinal characteristics have a greater impact on travel behavior compared to land use.

Fang (2008) examined the influence of residential density on passenger and freight trips. The author used data from the 2001 National Household Travel Survey for California and concluded that a 25% increase of density results in a decrease of 309.8 miles annually for freight transportation, while the decrease in annual miles travelled by cars per household is 64.6 miles.

Holtzclaw (1994) determined the influence of neighborhood characteristics on motor vehicle usage per household, expressed as autos per household (HH), and total vehicles miles travelled annually per household (VMT/HH) by analyzing twenty eight communities in California.

The following equations were developed in order to predict autos/ HH and VMT/HH

$$\text{Autos/HH} = 2.704 * \text{density}^{-0.25} \quad \textbf{(2.8)}$$

$$\text{VMT/HH} = 34.270 * \text{density}^{-0.25} * \text{TAI}^{-0.076} \quad \textbf{(2.9)}$$

where TAI: transit accessibility index

The autos/ HH depend only on density while the VMT/HH is influenced by the density of area but also by the transit accessibility. According to the author, double density results in 25-30% less driving per family when the impacts of all the conditions accompanying higher density (such as better transit or more local shopping) are included. Moreover, this study found that when the neighborhoods in which people live and their characteristics are taken into account, the income fails to provide statistically significant results and explain increases or decreases of VMT. In conclusion, VMT/HH increases as household density and the transit, shopping and pedestrian indices decrease.

2.2.3 VMT and lane miles

Noland (2001) examined the effect of lanes miles on the amount of VMT, using cross-sectional time series of 50 US states from 1984-1996. The lane miles were statistically significant variable with elasticity around 0.287 for the sum of VMT. The author also estimated the effect of population and income (both factors had high effect: elasticity around 1) and the effect of fuel cost which was much lower on travel demand. The author developed a model of simultaneous equation estimations, assuming that the amount of VMT in a road affects the amount of VMT in another road. The equations had the following form:

$$\log\,(VMT_{itr})=c+\alpha_i+\sum\beta^k(X_{it}{}^k)+\lambda\log(LM_{itrl})+\varepsilon_{it} \quad \textbf{(2.10)}$$

where

VMT_{itr} : VMT in state *i*, for year *t*, by road type *r*

c: constant term

α_i: fixed effect for state *i*

β^k: coefficients to be estimated (for demographic and other parameters)

λ: coefficient to be estimated fro LM parameter

X^k_{it} : value of demographic and other variables for state, *i*, and time, *t*

LM_{itrl} : proxy for cost of travel time (lane miles) by state, *i*, for year, *t*, for road type, *r*, lagged by *l* years

ε_{it} : random error term

It is interesting that the coefficient for lane miles was higher in the equation developed for collector roads while the fuel cost and the income affected more the VMT on interstates. The author concluded that the increased capacity contributes to the increase of VMT, and that its contribution is about of one quarter of the total growth of VMT. Urban roads had a more significant relationship with VMT growth compared to rural roads and the only unexpected result was the elasticity of VMT with respect to lane miles of collectors, which was larger than that for arterials and interstates.

Fulton et al. (2000) used data from the Energy and Environmental Analysis (EEA) of 1999 and examined the effect of increased capacity on VMT. Their study focused on 4 states and 5 geographic areas, using data at the county level for: Maryland, North Carolina, Virginia, Washington, D.C./Baltimore metropolitan area, and all the states and D.C. together. The variable representing the lane-miles was significant in all the developed models while the coefficient was around 0.3-0.6. Interestingly, the lowest coefficient for the lane-miles was found for the D.C/ Baltimore metropolitan area.   The coefficients for population growth and per capita income were significant for the D.C/ Baltimore metropolitan area but they were not different in magnitude, compared to the overall results. Also the coefficient for population growth was consistently and highly significant across the models, while the coefficient for income per capita varied more and was much less significant across the models. In the model developed for all states, the lane-mile coefficient was slightly larger compared to the models for individual states. In conclusion, and after controlling for population and income, a 10% increase in lane-miles would result in a 3-6% increase in daily VMT in the Mid-Atlantic region.

The Transportation Research Board (1995) examined the effect of induced travel on air quality and energy use. According to this report, the decrease in travel time resulted in increase in VMT by increasing highway use, and at the same time affects urban development. Moreover, Noland and Cowart (2000), using nationwide metropolitan data, showed that the long run elasticity for lane-miles is around 0.8-1.0 for interstates and arterial roads.

Strathman et al. (2000) used the 1995 Nationwide Personal Transportation Survey (12,000 households were included) and the Texas Transportation Institute (TTI) data and examined the effect of road capacity on VMT for 48 different metropolitan areas. It was found that per capita roadway has a significant effect not only on VMT, but also on mode choice, residential and workplace density. The elasticity for roadway capacity was equal to 0.29. Moreover, the authors indicated that there is an indirect effect on VMT through the residential and employment density. The indirect elasticity of these two factors was around 0.033 for roadway capacity and VMT, almost one-tenth of the magnitude of the direct effect.

2.2.4 VMT and race/ethnicity

Contrino and McGuckin (2009) examined the influence of race/ethnicity on VMT. A high percentage of African-American, Hispanic and Asian households have no vehicle, fact that results directly to a decrease of their mobility. While the percentage of households in U.S with no vehicle is around 10.3%, the percentage of households with no vehicle for African-American is 23.8%. Moreover, the African-American and Asian women have much lower rates of licensure compared to males. The Hispanic households produce the greatest amount of travel per household annually but at the same time the number of trips per person is among the lowest. The main reason for this is the higher size of household. Moreover, Hispanic households have the highest vehicle occupancy, equal to 1.8 persons per vehicle. Lastly, Blacks, Asians and Hispanic are in general more frequently users of alternative modes of transportation (transit, walking), that results directly in a decrease of VMT.

2.3 Summary

This chapter reviewed previous studies on travel demand and the factors that influence demand. According to these studies, the Vehicle Miles Traveled are affected by demographic and socio-economic factors. In general, income and population growth are the most significant factors influencing travel demand, followed by age, gender, household size and race/ethnicity. Moreover, the number of workers in the household and the ratio of female workers to male workers contribute to VMT changes. The number of vehicles in a household and the vehicle availability affect mode choice and subsequently, VMT. Turning to the effect of land use on VMT, the development of a city (urban and rural population density) affects the number of trips but also trip length and travel mode and as such has a direct and indirect influence on VMT. Urban development typically results in less amount of VMT while in rural areas or less dense areas the amount of VMT is higher. Lastly, highway capacity and travel time also influence the amount of trips and VMT.

Table 2.1 presents a summary of select studies that have estimated the elasticity of VMT with respect to various factors. Note that previous studies that resulted in only qualitative conclusions are not included in Table 2.1.

Table 2.1: Summary of Select Studies

Study, Authors, Year	*Study area*	*Methodology*	*Factors*	*Elasticity*
Congressional Budget Office, 2008	National level		fuel price-short run elasticity	-0.6%
			fuel price-long run elasticity	-4%
Heanue, 1997	Milwaukee Wisconsin	Analysis and observations of existed data	population	78%
			household characteristics	
			income	
			auto ownership	
			total employment	
			% of women in employment	
			gasoline prices	
			density	
			highway capacity	6-22%
Barr, 2000 $Log(VMT_i)=\alpha+\sum\beta_k log(X_i)+\varepsilon_i$	National Level	Linear Regression	travel time	-4.37%
			highway capacity	3.50%
			income	3.50%
			family members	5-25%
			workers in the family	20-33%
			density	-5%
Mabe, 2007 $Qdrive= aInc^{\beta inc}*Psub^{\beta Psub}/ Pdrive^{\beta Pdrive}$	National Level	Multivariate regression and time series analysis	income	1.60%
			cost of driving	-
			cost of substitute	0.13%
Hu et al, 2000 log (VMT)= constant+ $\alpha_1$log(income) + α_2(fuel price) + α_3(health status) + α_4(employment status)+ α_5(other drivers available in household) + α_6(year)	National Level	Regression model	income	0.305%
			fuel price	-2%
			health status	0.0868%
			employment status	0.4991%
			number of drivers	-0.1279%
			year	0.0218%
Noland, 2001 $log(VMT_{itr})=c+\alpha_i+\sum\beta^k(X_{it}^k)+\lambda log(LM_{itrl})+\varepsilon_{it}$	National Level	Log-log regression model Simultaneous Equations	fuel price	-0.126%
			income	1.075%
			population	1.074%
			lane-miles	0.287%

Table 2.1 (Continued)

Study, Authors, Year	*Study area*	*Methodology*	*Factors*	*Elasticity*
Fulton et al., 2000 $\log(VMT_{it})=c+\alpha_i+\beta_t+\sum\lambda^k \log(X^k_{it})+\varepsilon_{it}$	Maryland, North Carolina, Virginia, Washington D.C.	Regression, Instrument Variables, Distributed Lag, Fixed Effects	lane-miles	0.3-0.6%
			population	
			Income	
Noland, Cowart, 2000	Nationwide Metropolitan Areas	Regression, Instrument Variables, Distributed Lag, Fixed Effects	lane-miles	0.8-1%
Strathman et al., 2000	48 Metropolitan areas	Regression-Instrument Variables	roadway capacity	0.29%
			density	-0.033%
			employment density	0.033%

CHAPTER 3 DESCRIPTION OF DATA

3.1 Data

Various data sources were used in this research. Data on VMT for the 48 continental states in the U.S. (excluding Alaska and Hawaii) from 1998-2008 were gathered from the Federal Highway Administration (FHWA) through the service Highway Performance Monitoring System (HPMS). HPMS was established in 1978 and provides information on the amount of VMT and percentage of trucks for each state every year by FHWA functional classification. Information on demographic (population, age, race) and socioeconomic factors (income, percentage of people working at home, density) was provided by CENSUS Bureau (CENSUS 1999, CENSUS 2000 and projections for 2000-2008). Data on fuel prices, fuel taxes, lane miles, level of congestion (volume over capacity ratio) and vehicle registrations was obtained from FHWA Highway Statistics. Last, data for alternative fuel vehicles was provided from the U.S Department of Energy and the Energy Information Administration.

3.2 Descriptive statistics

Table 3.1 shows the descriptive statistics of the variables considered in this thesis. The table also includes the mean and standard deviation of the highway network and congestion variables by functional class.

Table 3.1: Descriptive statistics of variables considered in this thesis

Variables	Mean or percentage	Standard Deviation	Number of observations
Vehicle Miles Traveled in Rural Areas (billions)			
Interstate	4.07	2.87	528

Table 3.1 (Continued)

Variables	Mean or percentage	Standard Deviation	Number of observations
Principal Arterial	4.26	3.31	528
Minor Arterial	3.08	2.47	528
Collector	3.79	3.10	528
Total VMT	15.2	11.05	528
Vehicle Miles Traveled in Urban Areas (billions)			
Interstate	7.89	10.08	528
Freeways	3.79	7.69	528
Other Principal Arterials	8.28	9.75	528
Minor Arterials	6.82	7.95	528
Major Collector	3.00	3.71	528
Total VMT	29.78	38.00	528
Population (in millions) (by state)	5.99	6.407	528
Percentage of urban population	67.03	15.51	528
Percentage of White population	79.09	10.19	528
Percentage of Black or African-American population	10.11	9.53	528
Percentage of Hispanic or Latino population	8.47	9.41	528
Percentage of Asian population	2.33	2.04	528
Population under 18 (in millions)	1.51	1.66	528
Population 65 and over	746516	768776	528
Percentage of male population	49.18	0.66	528
Percentage of female population	50.82	0.66	528
Income per capita	31020.8	5858.52	528
Percentage of people working at home (telecommuting)	17.25	11.41	432
Fuel cost (cents/ gallon)	192.69	68.47	526
Fuel tax-State (cents/ gallon)	20.85	4.85	528
Fuel tax-Federal (cents/ gallon)	18.4	0.00	528
Total fuel tax (cents/ gallon)	39.25	4.85	528
Density (population per square mile)	189.05	253.84	528
Vehicle registration (in millions)	2.80	3.16E	528
Vehicle per capita	0.46	0.07	528

Table 3.1 (Continued)

Variables	Mean or percentage	Standard Deviation	Number of observations
Percentage of alternative fuel vehicles	0.23	0.15	528
Lane miles-Rural			
Interstate	642.29	386.30	528
Principal arterial	2002.06	1228.4	528
Minor arterial	2824.17	1939	528
Collector	8834.17	6801.41	528
Total	14302.7	9847.39	528
Lane miles-Urban			
Interstate	302.53	258.85	528
Freeways	206.35	291.63	528
Other Principal arterial	1196.13	1200.28	528
Minor arterial	1988.52	1933.05	528
Major Collector	2028.49	2125.44	528
Total	5722.02	5710.2	528
V/C-Rural Interstate[*]			
0.80-0.95	24.61	41.60	528
>0.95	10.82	19.85	528
Percentage of congested miles	7.61	11.74	517
V/C-Rural Principal arterial[*]			
0.80-0.95	21.20	33.27	528
>0.95	19.21	30.31	528
Percentage of congested miles	3.02	5.09	528
V/C-Rural Minor arterial[*]			
0.80-0.95	18.23	51.36	528
>0.95	16.49	38.78	528
Percentage of congested miles	1.74	3.38	528
V/C-Rural Collector[*]			
0.80-0.95	12.54	43.83	528
>0.95	10.32	30.93	528
Percentage of congested miles	0.37	0.9	528
Percentage of congested miles in rural	1.42	1.96	528
V/C-Urban Interstate[*]			

Table 3.1 (Continued)

Variables	Mean or percentage	Standard Deviation	Number of observations
0.80-0.95	52.59	63.30	528
>0.95	60.90	84.94	528
Percentage of congested miles	30.28	18.72	528
*V/C-Urban Freeways**			
0.80-0.95	26.63	54.32	528
>0.95	29.43	67.22	528
Percentage of congested miles	20.19	15.54	477
*V/C-Urban Other Principal arterial**			
0.80-0.95	83.99	102.34	528
>0.95	75	102.68	528
Percentage of congested miles	11.71	7.72	528
*V/C-Urban Minor arterial**			
0.80-0.95	102.77	136.58	528
>0.95	111.55	141.16	528
Percentage of congested miles	9.34	5.76	528
*V/C-Urban Major Collector**			
0.80-0.95	61.97	92.92	528
>0.95	78.18	111.56	528
Percentage of congested miles	5.86	4.01	528
Percentage of congested miles in urban	10.05	4.99	528

**V/C: volume per capacity ratio*

3.3 Demographics and socioeconomics characteristics

Figure 3.1 shows the growth of population during the analysis period. Population grew at the same rate over the years, while a different trend applies for income per capita (Figure 3.2). The income per capita has increased during the past11 years in United States. Figure 3.3 shows the growth of urban population from 2001. Overall, the percentage of urban population ranges from 72 to 80 percent during the analysis period.

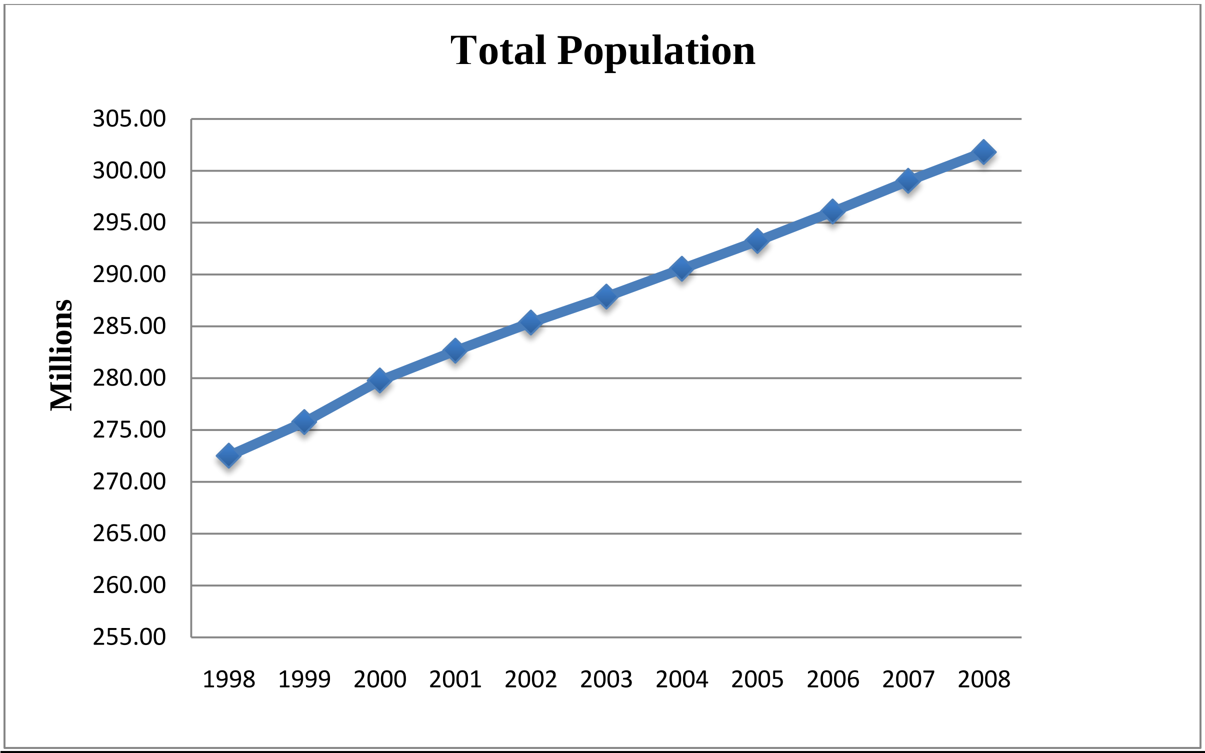

Figure 3.1: Total population in U.S (1998-2008)

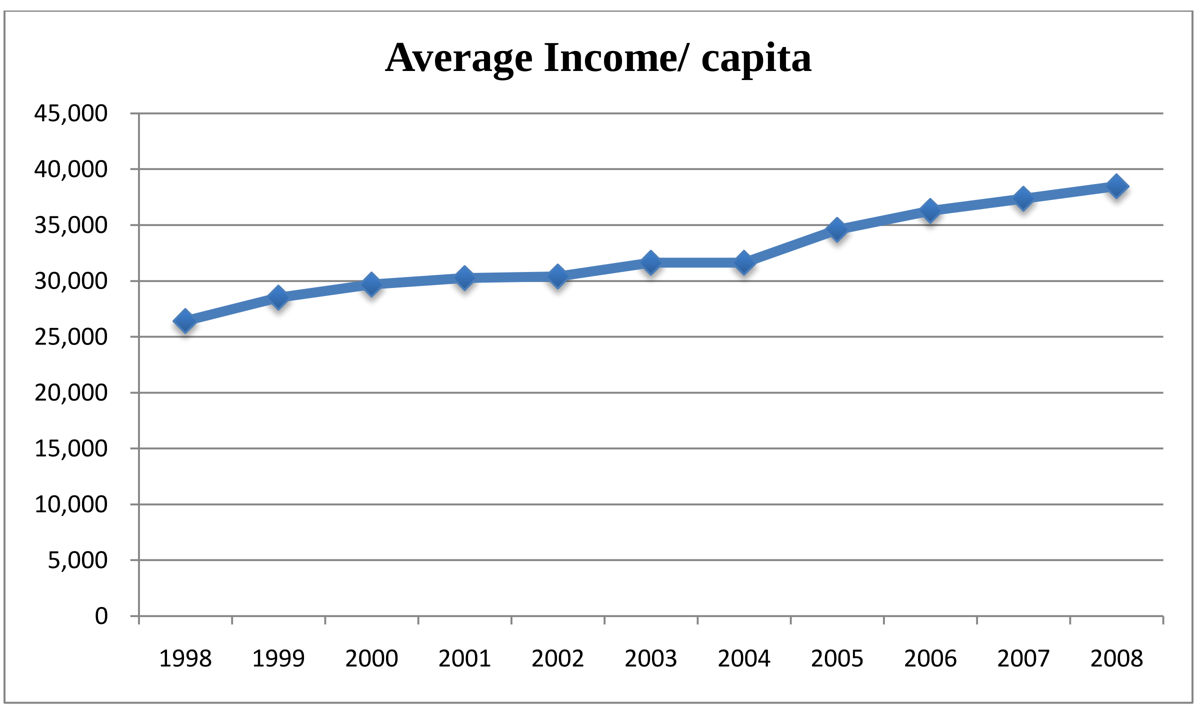

Figure 3.2: Average income per capita (1998-2008)

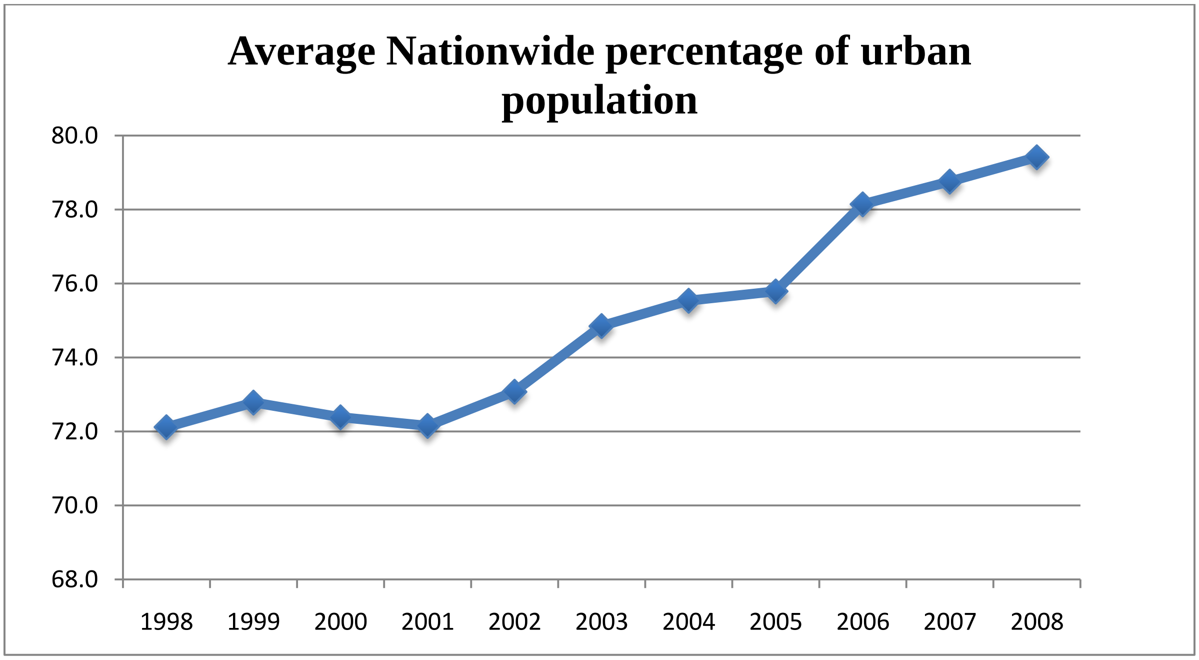

Figure 3.3: Average percent of urban population (1998-2008)

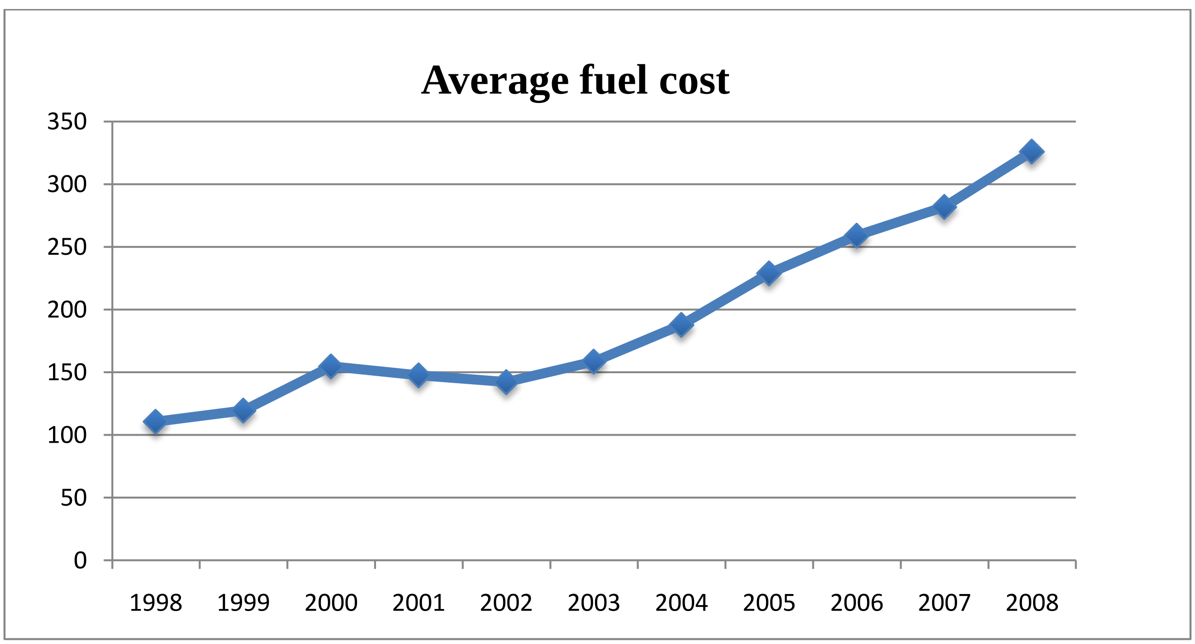

Figure 3.4: Average fuel cost (1998-2008)

Figure 3.4 shows that fuel cost has increased since 1998, with the increase being higher during recent years, and especially after 2004. Figure 3.5 shows a peak in vehicle registrations in 2001, and no steady trend ever since. The vehicles that are included in the vehicle registrations are only automobiles (private and public).

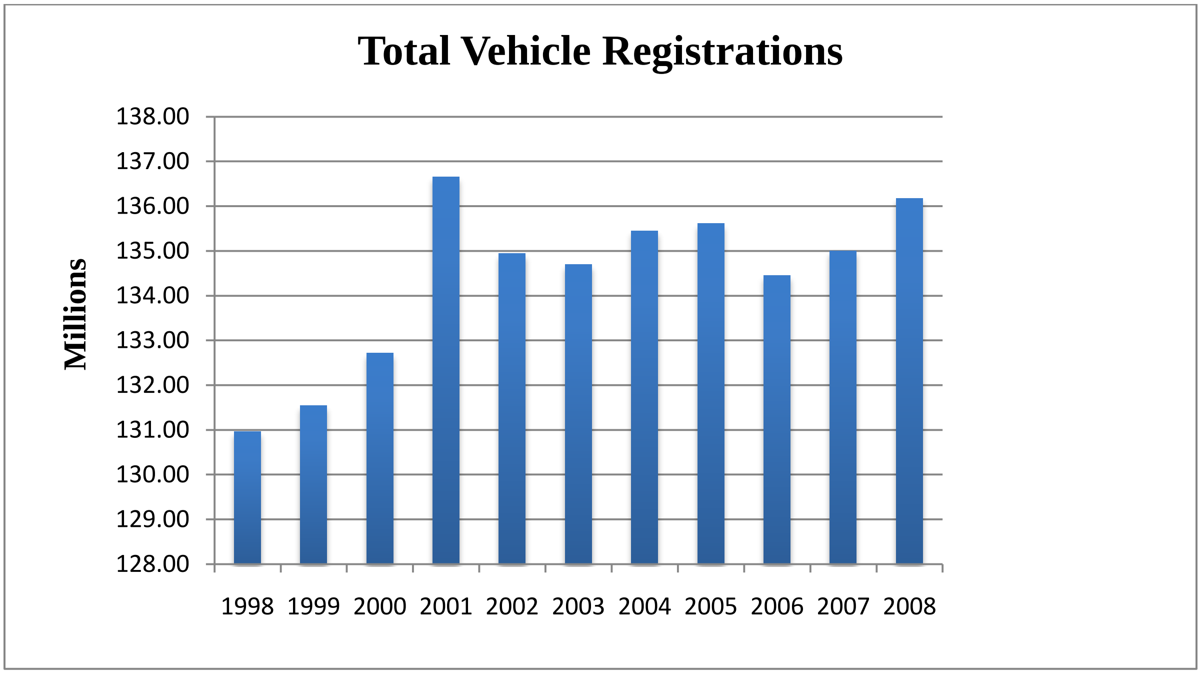

Figure 3.5: Total vehicle registration (1998-2008)

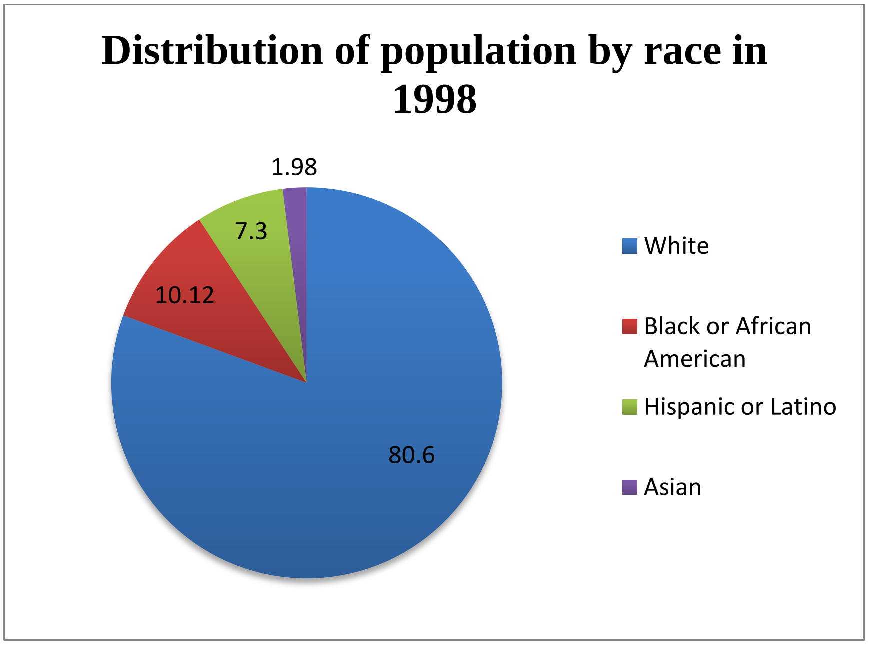

Figure 3.6: Distribution of population by race in 1998

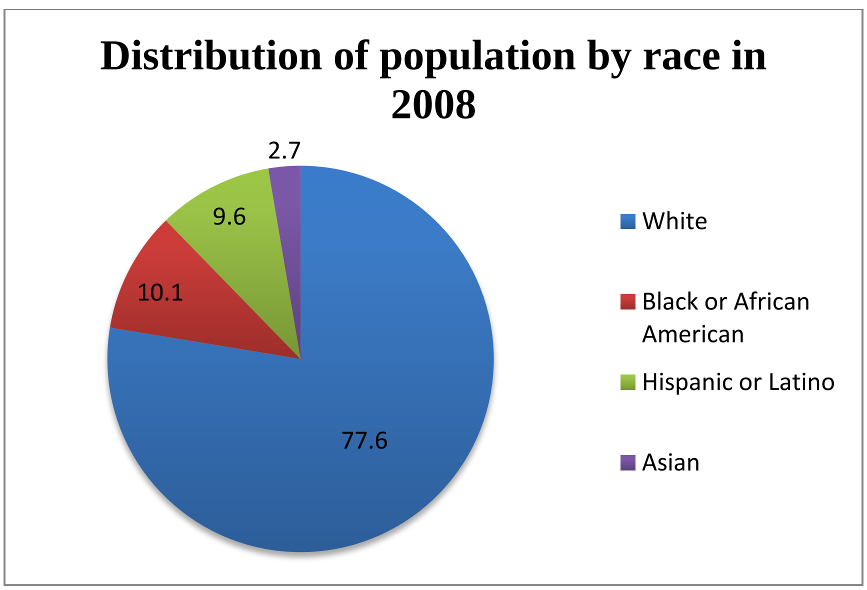

Figure 3.7: Distribution of population by race in 2008

Figures 3.6 and 3.7 show the distribution of population by race in 1998 and in 2008. The Hispanic population experienced the greatest increase during the decade 1998-2008, comparing to the other minority populations.

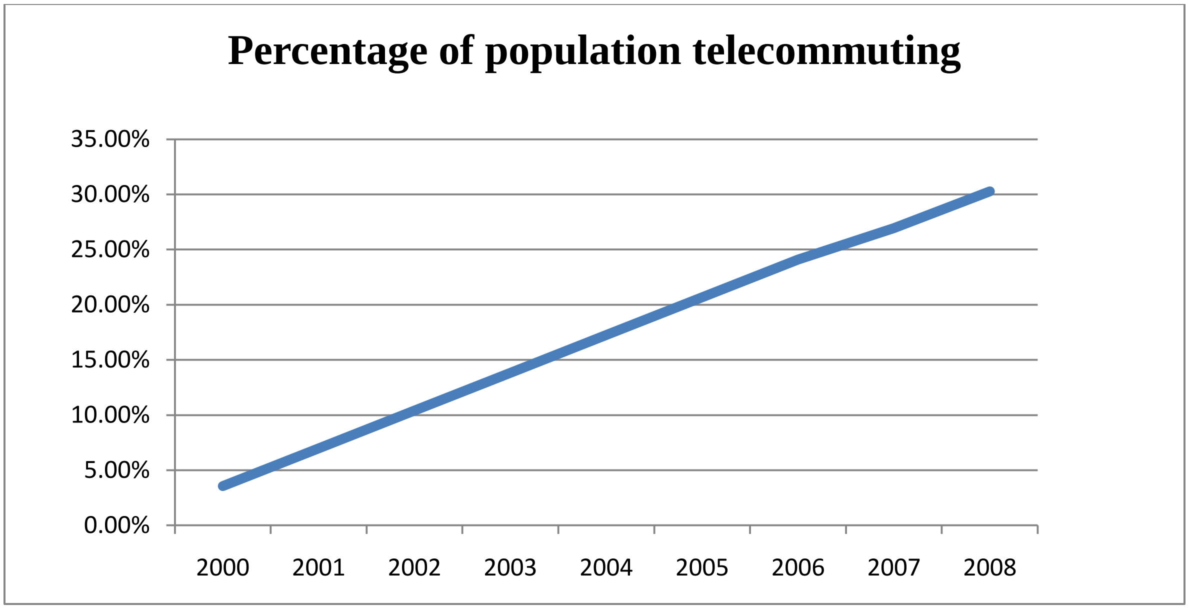

Figure 3.8: Percentage of population working at home (2000-2008)

The percentage of people working at home has increased by five times since 2000 (Figure 3.8), mainly due to the increased use of the internet that has enabled and improved telecommuting.

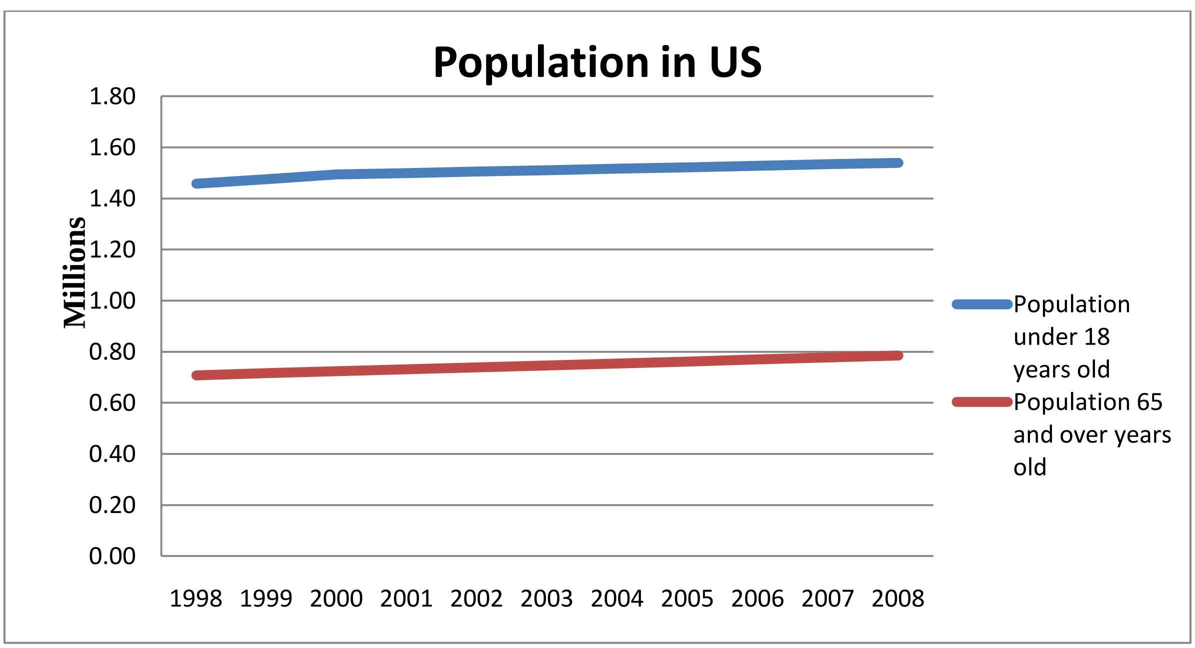

Figure 3.9: Population under 18 years old and population 65 and over years old (1998-2008)

Figure 3.9 shows that the population of people 65 and older has increased at a faster rate than the population of people under 18 years old (young population). Figure 3.10 shows the percentage of male and female population. The distribution of population by gender has not changed during the past 10 years (1998-2008).

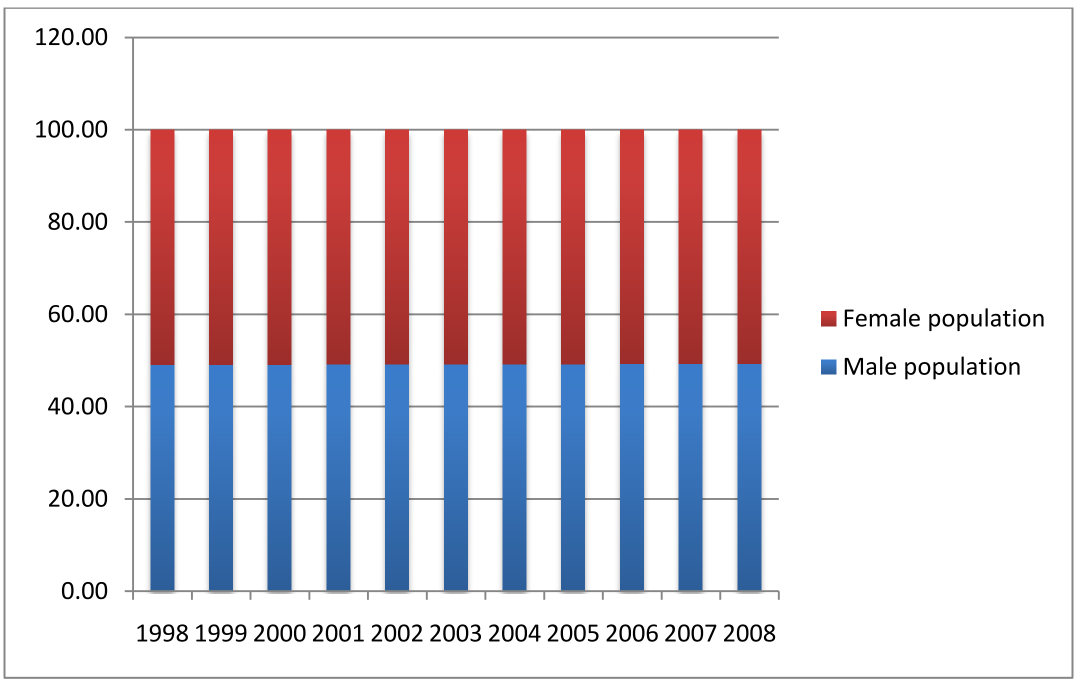

Figure 3.10: Distribution of population by gender (1998-2008)

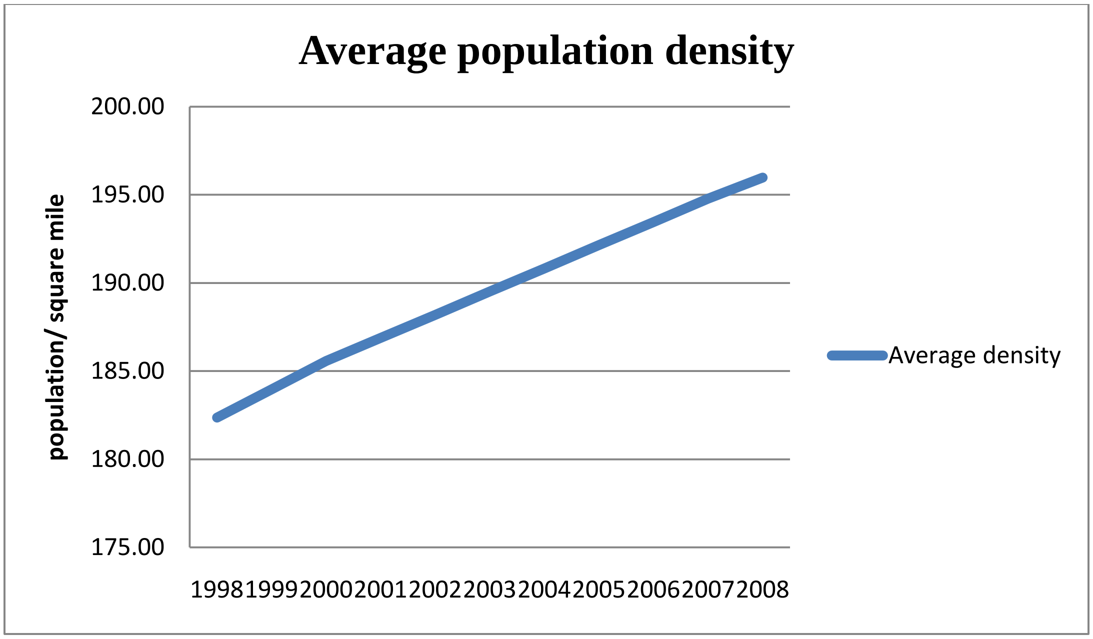

Figure 3.11: Average density (1998-2008)

As the population has increased from 1998 to 2008, the average density (population per square mile) has increased as well (Figure 3.11).

3.4 Vehicle Miles Traveled

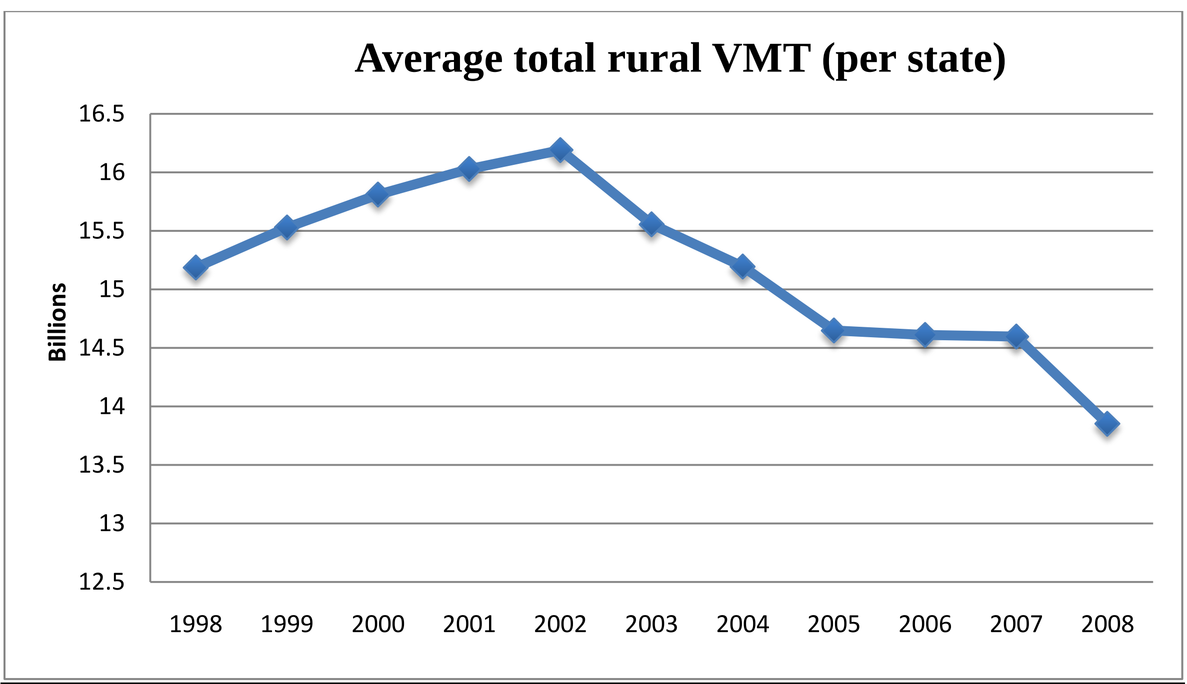

Figure 3.12: Average total rural VMT (1998-2008)

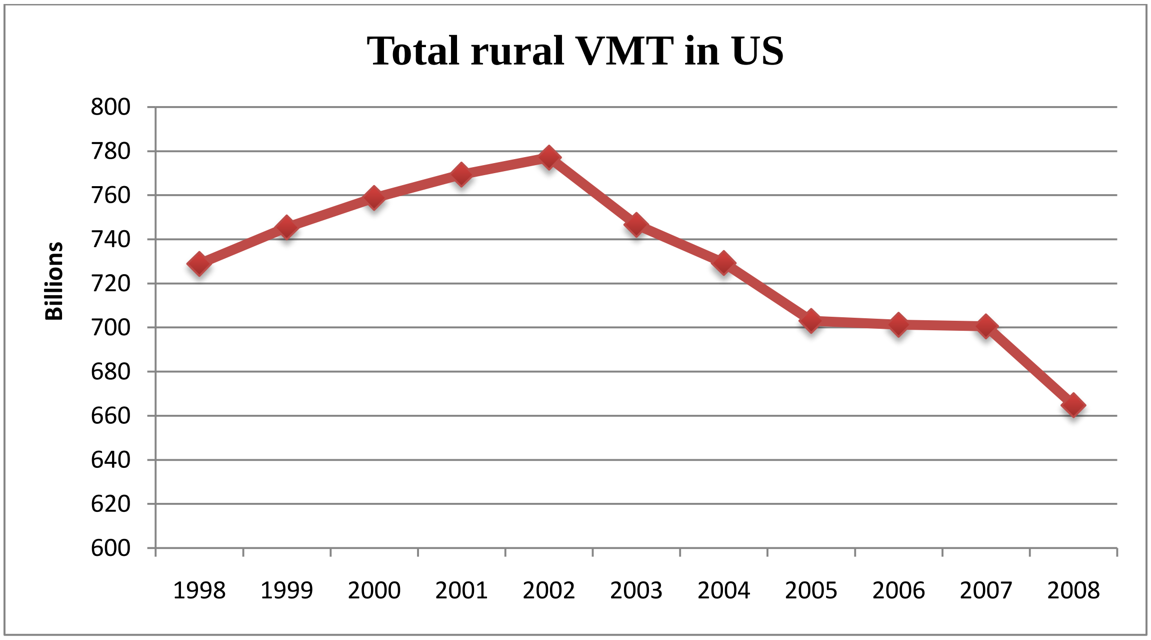

Figure 3.13: Total rural VMT (1998-2008)

The average total rural VMT (Figure 3.12) is calculated by dividing the total amount of rural VMT per year by the number of states (48). In this way, an average amount of total rural VMT (includes all the different functions of rural road) is estimated each year. The total rural VMT (Figure 3.13) represents the total amount of VMT for all states and all functions of rural roads every year. The same methodology was applied in order to estimate the average total urban VMT (Figure 3.14) and the total urban VMT (Figure 3.15).

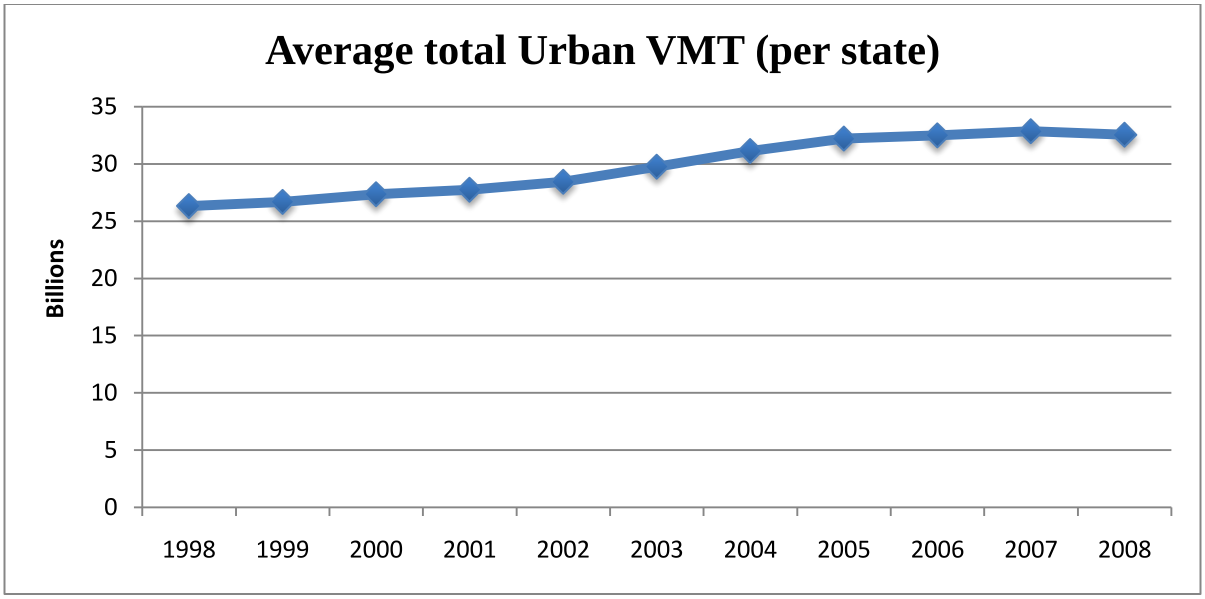

Figure 3.14: Average total urban VMT (1998-2008)

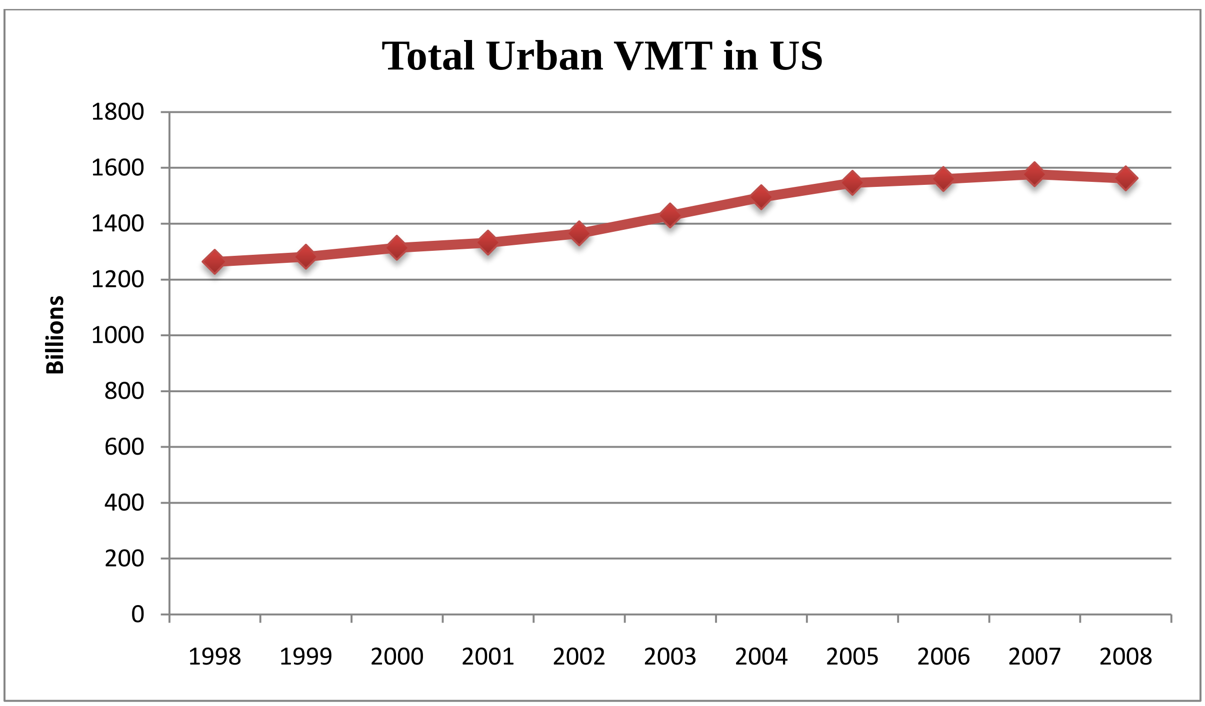

Figure 3.15: Total urban VMT (1998-2008)

As it is observed in Figures 3.12-3.15, the rate of increase for average VMT is the same with the rate of increase for total VMT for both rural and urban areas.

3.5 Road Network

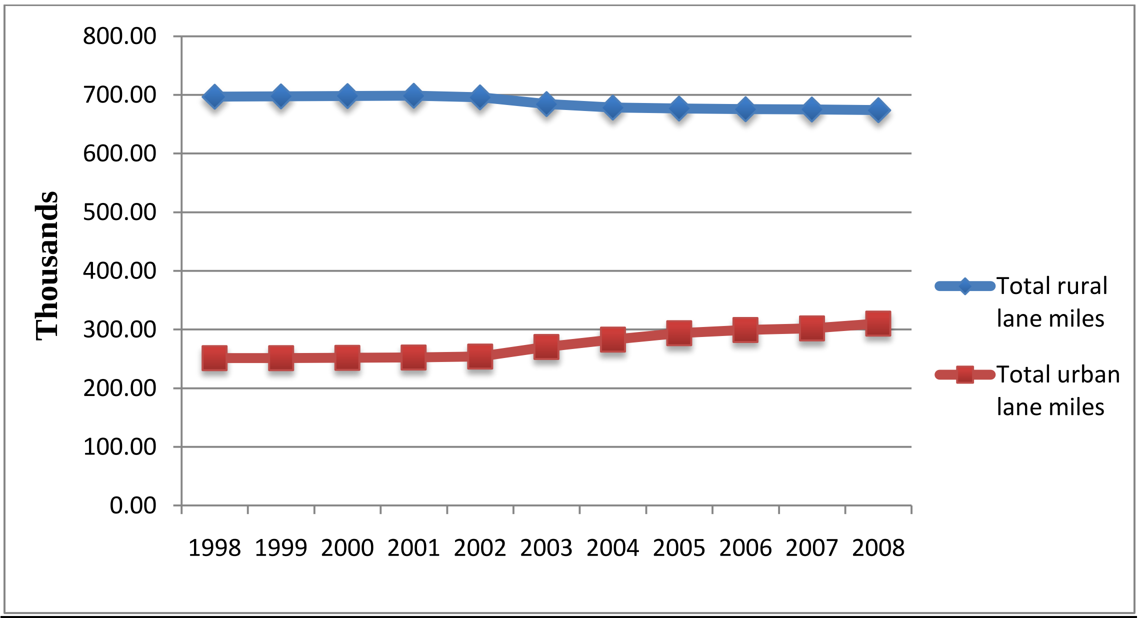

Figure 3.16: Total rural lane miles and total urban lane miles in US (1998-2008)

Figure 3.16 shows the length of the road network. The total number of rural lane miles has decreased by a small amount while the urban road network has been extended by a greater amount. The total amount of the network has increased, as it is shown in Figure 3.17. However, this increase has not been constant during the years. Figure 3.18 shows the total congested miles for urban and rural roads. It is evident and expected that the amount of congested miles in urban areas is much higher that the amount of congested miles in rural areas.

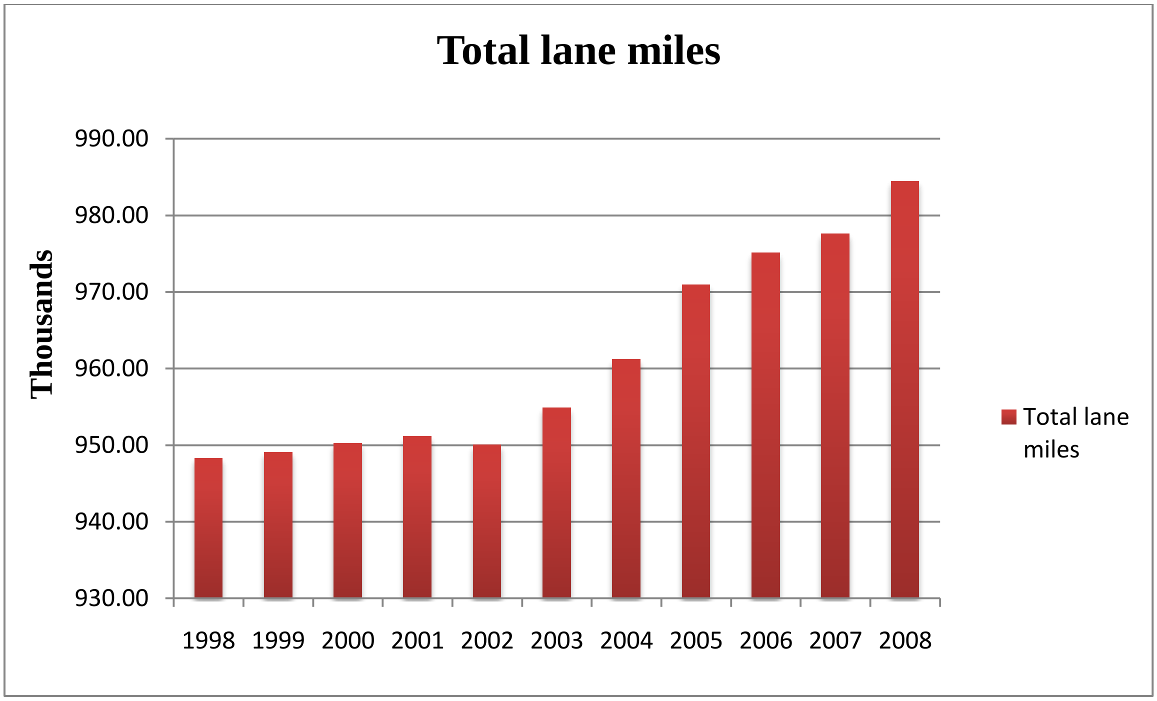

Figure 3.17: Total lane miles (1998-2008)

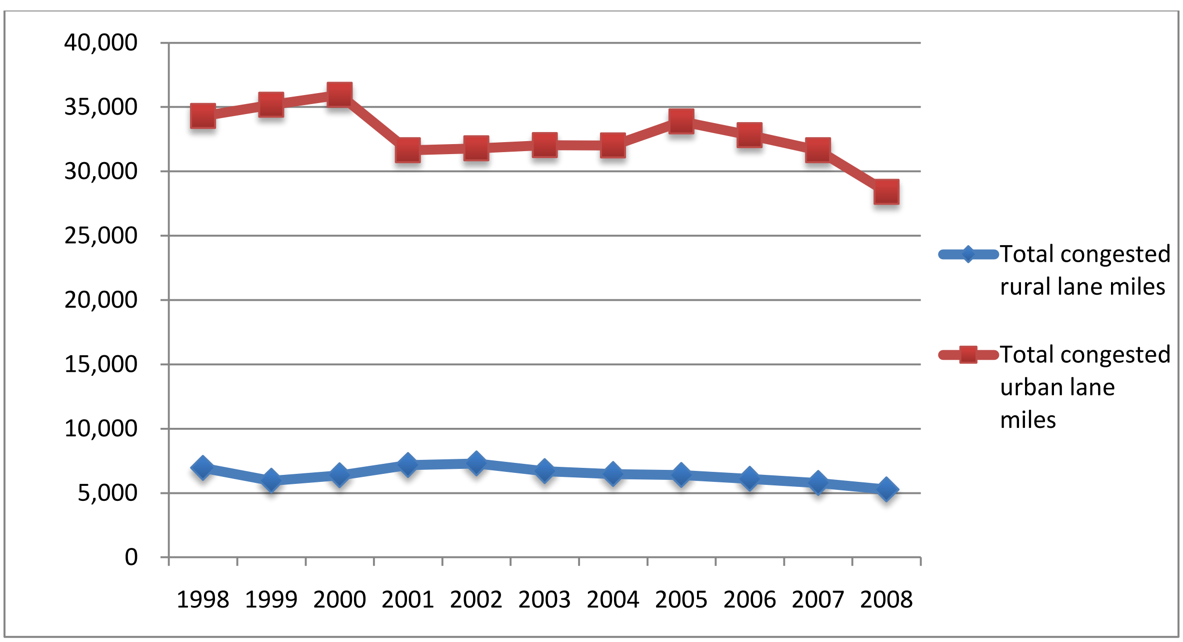

Figure 3.18: Total congested miles for rural and urban roads (1998-2008)

3.6 Select Statistics by Region

Recognizing that driving patterns differ from region to region, this Section presents VMT and population trends by region over the study period. The classification of states in regions considered in this study is the following:

1) Northeast: Maine, New Hampshire, Vermont, Massachusetts, New York, Rhode Island, New Jersey, Connecticut, Pennsylvania

2) South: Maryland, Delaware, Virginia, West Virginia, Kentucky, North Carolina, South Carolina, Tennessee, Arkansas, Georgia, Alabama, Louisiana, Florida, Oklahoma, Texas

3) Midwest: North Dakota, South Dakota, Nebraska, Kansas, Missouri, Iowa, Minnesota, Wisconsin, Illinois, Indiana, Ohio, Michigan

4) West: Washington, Idaho, Montana, Oregon, Wyoming, California, Nevada, Utah, Colorado, Arizona, New Mexico.

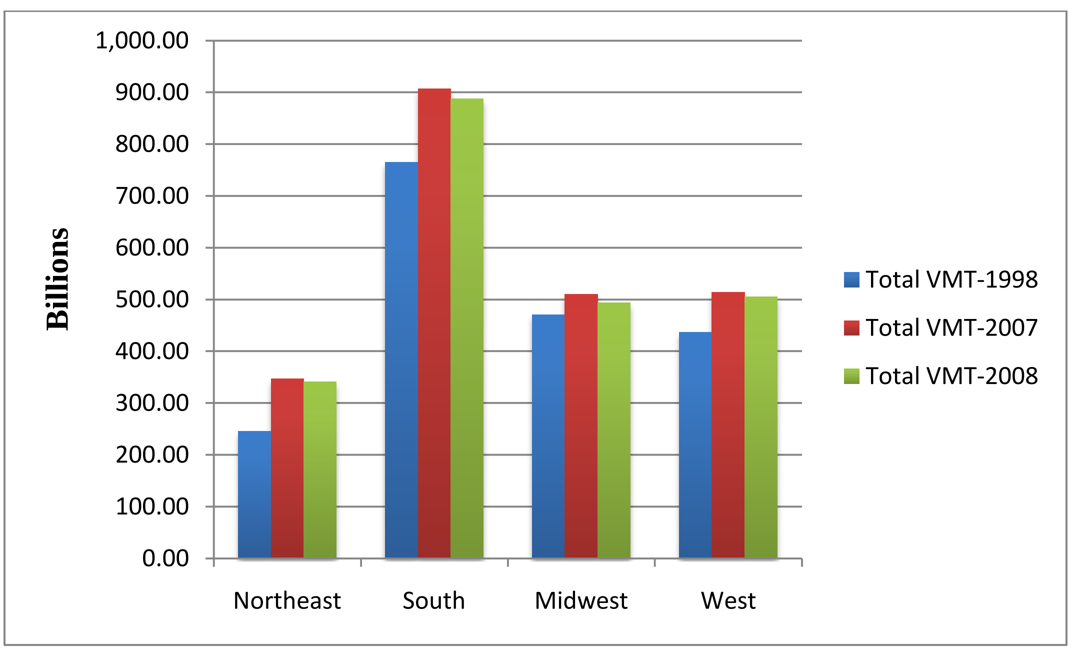

Figure 3.19: Total VMT (urban and rural) by region for 1998, 2007 and 2008

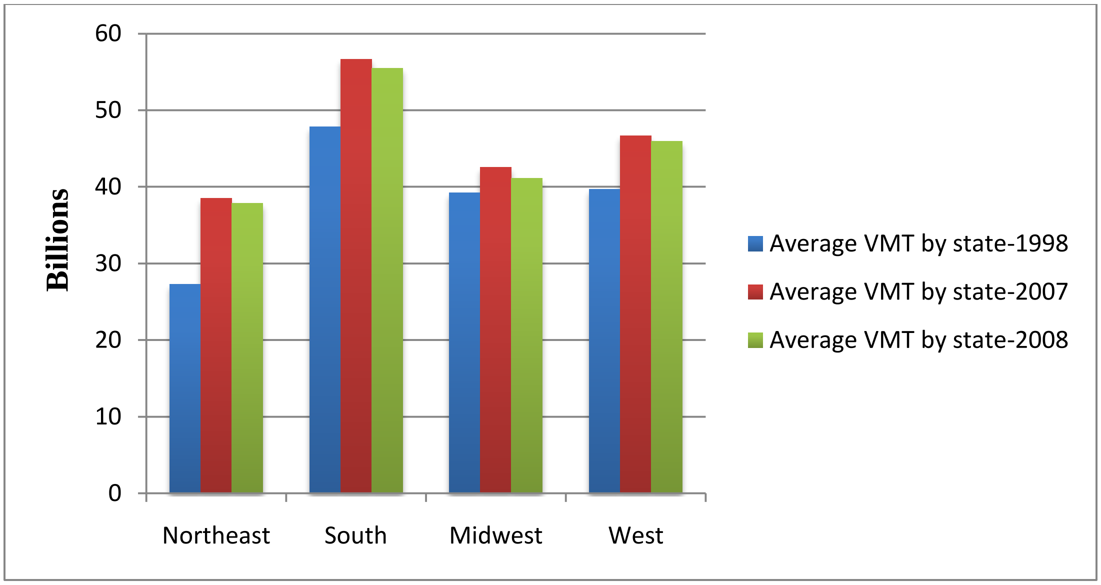

Figure 3.20: Average VMT (urban and rural) by state by region for 1998, 2007 and 2008

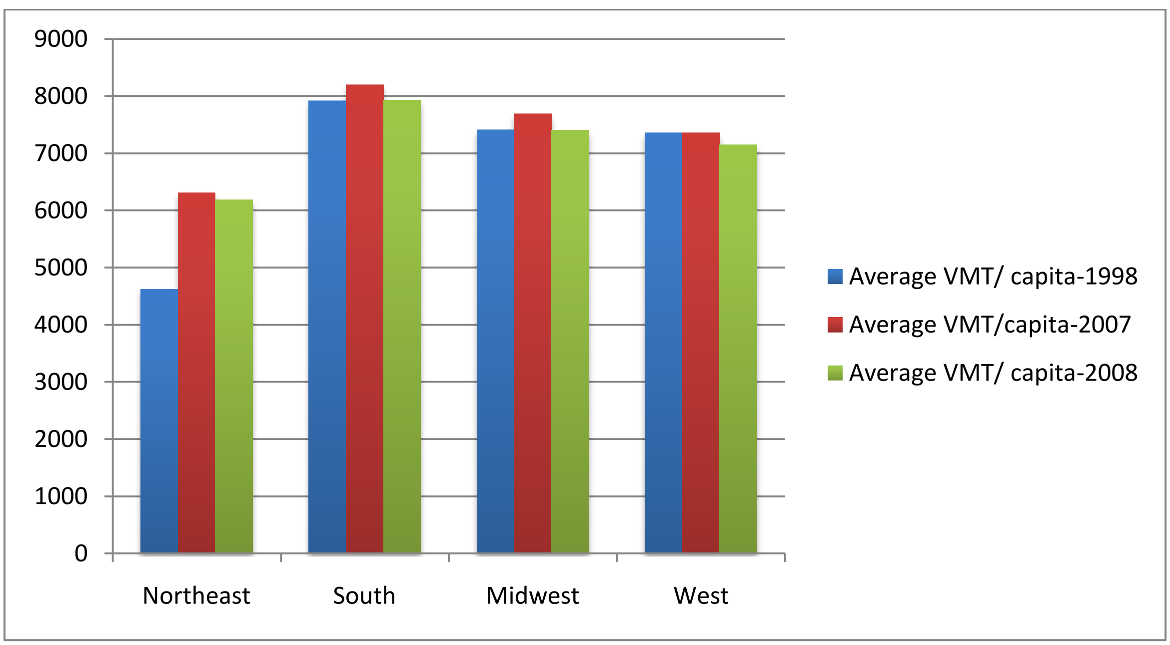

Figure 3.21: Average VMT (urban and rural) per capita by region for 1998, 2007 and 2008

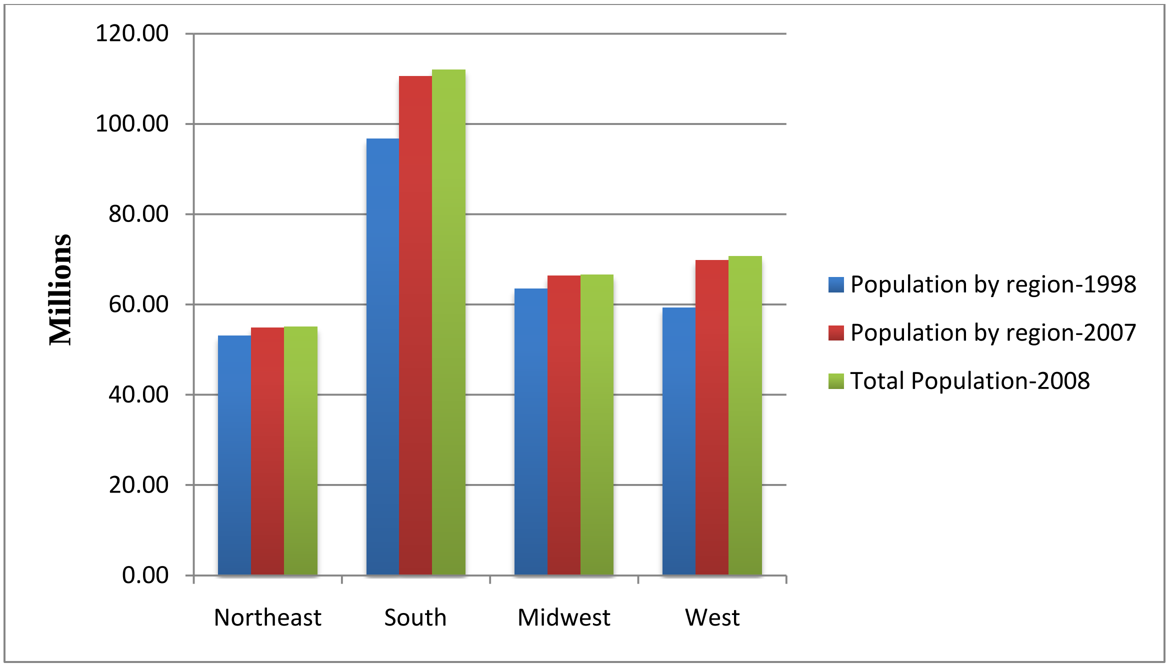

Figure 3.22: Population by region for 1998, 2007 and 2008

It can be observed that VMT increased from 1998 to 2007 and decreased in 2008, because of the high fuel prices. The decrease is similar for all the regions and it is constant with the decrease of total VMT, shown in figures 3.13 and 3.15. Moreover, according to Figure 3.19, the South region experiences the highest amount of VMT, VMT per state and VMT per capita among all regions. These observations are consistent with results from previous studies which indicated that people in the South tend to travel more by car due to good weather and also due to the absence of an extended transit network (Puentes and Tomer 2008). On the other hand, the Northeast region experiences the lowest amount of total VMT, VMT per state and VMT per capita. The Northeast region consists of small-sized states, so the distances between cities and adjacent states are fairly low and so is the amount of VMT. Moreover, the large number of metropolitan areas in that region and the availability of an extensive transit network, contributes to a lower amount of VMT per capita. The Midwest and West regions have similar amount of VMT and VMT per capita and VMT per state. Lastly, the total population is similar in these two regions.

CHAPTER 4 METHODOLOGY-ANALYSIS OF RESULTS

4.1 Methodology

Vehicle Miles Traveled (VMT) is a continuous variable that can take on several values. So, as the dependent variable is continuous a linear regression model will be developed in order to determine the factors affecting VMT. As data for different years and places have been gathered, the data will be analyzed as panel data, in order to include the influence of different places and years on the amount of trips and the factors affecting it. Last, as the determination of elasticity for each variable is within the scope of this work, the log –linear regression will be estimated.

4.1.1 Simultaneous Equation Models

In many cases transportation data are better modeled using a system of interrelated equations instead of single equations for each dependent variable. Simultaneous equations models should be used in cases where the dependent variable of one equation is the independent variable of the other equation or in cases that the dependent variables are correlated. If these variables are analyzed separately, correlation between regressors and disturbances will be revealed and the key assumptions of best linear unbiased estimators will be violated (Washington et al., 2003).

4.1.1.1 Seemingly Unrelated Equations (SURE)

Seemingly Unrelated Equation (SURE) model is a category of Systems of Equation Models that it is applied in cases that the dependent variables are considered as a group but do not have a direct interaction as the variables in simultaneous equations have. This model is appropriate in cases that the factors that influence the dependent variables are the same or the dependent variables have some common characteristics. In that case, the equations are seemingly unrelated but there will be contemporaneous correlation of error terms. If the equations are estimated separately by Ordinary Least Squares (OLS), the coefficients are consistent but not efficient. Efficient parameters can be achieved only by considering the contemporaneous correlation among the disturbances (standard error) (Washington et al., 2003). The equation for seemingly unrelated models is:

$$y_i = X_i \beta_i + \varepsilon_i, i = 1, \ldots, M \tag{4.1}$$

where

y_i : T x 1 vector of observed values on the ith dependent variable,

X_i : T x p_i matrix with rank p_i of observations on p_i independent variables,

β_i : p_i x 1 vector of unknown regression coefficients

ε_i : T x 1 vector of error terms. It is assumed that $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_M)$ has a multivariate normal density with mean E[$\boldsymbol{\varepsilon}$] =**0** and covariance E[$\boldsymbol{\varepsilon\varepsilon}'$] = $\sum \otimes \boldsymbol{I}_T$ =**V.**

Estimation of SURE models is accomplished using Generalized least squares (GLS).

The Seemingly Unrelated Equation model (SURE) was selected for the analysis of VMT on different functional classes for rural and urban roads. This type of model was considered as appropriate for this case, as the amount of VMT on different functional classes either on rural or urban roads are highly correlated, as indicated in Tables 4.1 and 4.2. These tables show the correlation among VMT for the various functional classes. The correlation ranges from 0.787 up to 0.973, a fact that makes essential the analysis of VMT as a system and not individual.

4.1.2 Panel Data Models - Random Parameters

The use of panel data models was chosen for the analysis of total VMT as this methodology provides various benefits. First of all, the use of panel data controls for heterogeneity. Panel data suggest that individual states are heterogeneous while the time-series and the cross-section studies do not control for heterogeneity, resulting in biased results. The major problem of time-series studies is the multicollinearity problem that does not exist in the case of panel data models. Also, the more informative the data, in case of panel data, the more reliable the results would be. Furthermore, the panel data models are better able to study the dynamics of adjustment as the cross-sectional distributions hide a multitude of changes. The panel data also are better able to identify and measure the influence of variables that are not detectable in pure cross-section or pure time-series data. Lastly, the panel data models allow us to construct and test more complicated behavioral models than purely cross-sectional or time-series data (Baltagi, 2005).

4.1.2.1 Panel data regression-The two-way error component regression

Linear regression is used to model a linear relationship between a continuous dependent variable and one or more independent variables. In case of panel data (two-way error component models) the equation of the panel data regression is written:

$$Y_{it}=\alpha+X'_{it}\beta+\mu_i+\lambda_t+\nu_{it},\ i=1,\ldots,n;t=1,\ldots,T. \qquad \textbf{(4.2)}$$

α: constant

X_{it}: set of explanatory variables, independent of v_{it} for all i,t.

μ_{it}: unobserved cross-sectional specific effect

λ_t: unobserved time effects

v_{it}: random disturbances

β: coefficients of explanatory variables

The two-way error component panel data regression simultaneously accounts for the effects of individuals (eg. different places, states) and the effect of time on the dependent variable. The μ and λ are assumed to be fixed parameters to be estimated and the v_{it} are random disturbances, following the usual regression assumptions (Washington et al., 2003). The two-way error component regression model is appropriate in order to estimate the influence of any time-specific effect that is not included in the regression. For example, it could account the effect of hurricane Katrina (2005) or the fuel prices on travel demand (Baltagi, 2005).

4.1.2.2 Random Parameters

The variables, estimated with panel data and two-way error models have constant coefficients. However, in many cases, the cross-sectional units examined possess different unobserved demographic and socioeconomic factors that result in response variables that vary over time and different cross-sectional units (Hsiao, 1986). A general approach allows for heterogeneity in slope coefficients of the equation but the challenge is to obtain a model that is sufficiently flexible without overparametrisation. The fixed effects slope coefficient approach, in which each unit has its distinct coefficient vector, suffers from degrees of freedom problems. In random parameters and random coefficients approach, specific assumptions are made about the distributions that each coefficient follows and the model is far more flexible and has more degrees of freedom (Biorn et al., 1998). If the model parameters are needed to account for individual cross-sectional unit heterogeneity and for specific time periods, the equation of the developed model should be written (Washington et al, 2003):

$$Y_{it}=\sum (\beta_k+\alpha_{ki}+\lambda_{kt})X_{kit}+u_{it} \quad \textbf{(4.3)}$$

and the random coefficients:

$$\beta_{kit}= \beta_k+\alpha_{ki}+\lambda_{kt} \quad \textbf{(4.4)}$$

The α_{ki} and λ_{kt} are allowed to be random variables and introduce proper stochastic specifications. The random coefficients reduce the number of parameters to be estimated substantially, while still allowing the coefficients to differ from unit to unit and/ or from time to time (Hsiao and Pesaran, 2004).

4.2 Correlation matrix

Table 4.1 and Table 4.2 show the correlation coefficients among the dependent variables (VMT for different functional classes by type of area), while Table 4.3 presents the correlation coefficients among the independent variables (socioeconomic characteristics).

Table 4.1: Correlation among VMT in rural roads

	Interstate	**Principal arterial**	**Minor arterial**	**Collector**
Interstate	1	0.886	0.902	0.787
Principal arterial	0.886	1	0.877	0.788
Minor arterial	0.902	0.877	1	0.855
Collector	0.787	0.788	0.855	1

Table 4.2: Correlation among VMT in urban roads

	Interstate	Freeways	Principal arterial	Minor arterial	Collector
Interstate	1	0.926	0.943	0.961	0.862
Freeways	0.926	1	0.889	0.903	0.793
Principal arterial	0.943	0.889	1	0.973	0.948
Minor arterial	0.961	0.903	0.973	1	0.931
Collector	0.862	0.793	0.948	0.931	1

It is obvious, in Tables 4.1 and 4.2, that the correlation among VMT is high, fact that indicates the need for a system equation instead of individual analysis. Since VMT on a functional class are highly correlated with VMT in another functional class, the VMT on these two roads are correlated and the increase or decrease of one affect the other. Moreover, the factors that affect VMT are common among the functional classes and this is why we use a SURE methodology for our analysis.

Table 4.3: Correlation matrix of independent variables

	Population	**Urban population**	**White**	**Black or African American**	**Hispanic or Latino**	**Asian**	**<18 years old**	**>65 years old**	**Male**	**Female**	**Income/ capita**	**Telecommuting**	**Fuel cost**	**Fuel tax**	**Density**	**Vehicles**	**Alt. fuel vehicles**
Population	1	0.526	-0.551	0.375	0.305	0.529	**0.997**	**0.990**	-0.150	0.150	0.184	-0.191	-0.021	-0.171	0.192	**0.980**	0.011
Urban	0.529	1	-0.437	0.133	0.462	0.643	0.514	0.541	-0.067	0.067	0.601	-0.212	-0.039	-0.019	0.595	0.530	0.171
White	-0.495	-0.437	1	-0.784	-0.414	-0.463	-0.499	-0.452	0.287	-0.287	-0.129	0.253	-0.003	0.320	-0.246	-0.467	-0.226
Black or African American	0.197	0.133	-0.784	1	-0.152	0.040	0.188	0.203	-0.562	0.562	-0.029	-0.345	-0.047	-0.310	0.185	0.176	-0.104
Hispanic or Latino	0.509	0.462	-0.414	-0.152	1	0.492	0.529	0.454	0.342	-0.342	0.158	0.055	0.089	-0.113	0.065	0.451	0.516
Asian	0.678	0.643	-0.463	0.040	0.492	1	0.676	0.617	0.082	-0.082	0.622	0.018	0.128	-0.043	0.413	0.703	0.198
<18 years old	**0.996**	0.514	-0.499	0.188	0.529	0.676	1	0.951	-0.019	0.019	0.214	-0.101	0.005	-0.176	0.147	0.976	0.034
>65 years old	**0.973**	0.541	-0.452	0.203	0.454	0.617	0.951	1	-0.129	0.129	0.244	-0.106	0.018	-0.162	0.214	0.959	-0.042
Male	-0.053	-0.066	0.287	-0.562	0.342	0.082	-0.019	-0.129	1	-1	-0.101	0.364	0.109	0.008	-0.532	-0.076	0.504
Female	-0.053	0.067	-0.287	0.562	-0.342	-0.082	0.019	0.129	-1	1	0.101	-0.364	-0.109	-0.008	0.532	0.076	-0.504
Income/ capita	0.237	0.601	-0.129	-0.029	0.158	0.622	0.214	0.244	-0.101	0.101	1	0.031	0.092	0.015	0.665	0.262	0.072
Telecommuting	-0.096	-0.212	0.253	-0.345	0.055	0.018	-0.101	-0.106	0.364	-0.364	0.031	1	0.742	0.120	-0.189	-0.101	0.194
Fuel cost	0.019	-0.039	-0.003	-0.047	0.089	0.128	0.005	0.018	0.109	-0.109	0.092	0.742	1	0.201	0.020	0.002	0.180
Fuel tax	-0.171	-0.019	0.320	-0.310	-0.113	-0.043	-0.176	-0.162	0.008	-0.008	0.015	0.120	0.201	1	0.001	-0.168	-0.036
Density	0.173	0.595	-0.246	0.185	0.065	0.413	0.147	0.214	-0.532	532	0.665	-0.189	0.020	0.001	1	0.199	-0.103
Vehicles	**0.980**	0.53	-0.467	0.176	0.451	0.703	0.976	0.959	-0.076	0.076	0.262	-0.101	0.002	-0.168	0.199	1	-0.104
Alt. fuel vehicles	0.011	0.171	-0.226	-0.104	0.516	0.198	0.034	-0.042	0.504	-0.504	0.072	0.194	0.180	-0.036	-0.103	-0.104	1

Table 4.3 (continued)

					Rural lane miles					Urban lane miles					
	Population	**Vehicles**	**< 18 years old**	**>65 years old**	**Interstate**	**Principal arterial**	**Minor arterial**	**Collector**	**Total**	**Interstate**	**Freeways**	**Principal arterial**	**Minor arterial**	**Collector**	**Total**
Population	1	**0.982**	**0.996**	**0.973**	0.309	0.464	0.594	0.344	0.455	**0.929**	**0.933**	**0.968**	**0.965**	**0.961**	**0.975**
Vehicles	**0.982**	1	**0.976**	**0.959**	0.539	0.396	0.537	0.279	0.386	**0.899**	**0.898**	**0.938**	**0.949**	**0.928**	**0.945**
<18 years old	**0.996**	**0.976**	1	**0.951**	0.638	0.489	0.618	0.378	0.489	**0.922**	**0.937**	**0.969**	**0.966**	**0.961**	**0.978**
>65 years old	**0.973**	**0.959**	**0.951**	1	0.559	0.415	0.524	0.269	0.383	**0.910**	**0.887**	**0.936**	**0.918**	**0.937**	**0.962**
Rural lane miles															
Interstate	0.309	0.539	0.638	0.559	1	0.761	0.755	0.631	0.733	0.643	0.565	0.676	0.596	0.671	0.652
Principal arterial	0.464	0.396	0.489	0.415	0.769	1	**0.872**	**0.849**	**0.918**	0.471	0.495	0.541	0.489	0.548	0.530
Minor arterial	0.594	0.537	0.618	0.524	0.761	**0.872**	1	**0.828**	**0.912**	0.605	0.570	0.644	0.636	0.628	0.642
Collector	0.344	0.279	0.378	0.269	0.651	**0.849**	**0.828**	1	**0.985**	0.445	0.408	0.459	0.446	0.444	0.454
Total	0.455	0.386	0.489	0.383	0.733	**0.918**	**0.912**	**0.985**	1	0.509	0.477	0.536	0.516	0.524	0.530
Urban lane miles															
Interstate	**0.929**	**0.899**	**0.922**	**0.910**	0.643	0.471	0.605	0.445	0.509	1	**0.857**	**0.945**	**0.946**	**0.934**	**0.956**
Freeways	**0.933**	**0.898**	**0.937**	**0.887**	0.565	0.495	0.570	0.408	0.477	**0.857**	1	**0.908**	**0.901**	**0.922**	**0.929**
Principal arterial	**0.968**	**0.938**	**0.969**	**0.936**	0.676	0.541	0.644	0.459	0.536	**0.945**	**0.908**	1	**0.967**	**0.979**	**0.992**
Minor arterial	**0.965**	**0.949**	**0.966**	**0.918**	0.596	0.489	0.636	0.446	0.516	**0.944**	**0.901**	**0.967**	1	**0.943**	**0.982**
Collector	**0.961**	**0.928**	**0.961**	**0.937**	0.671	0.548	0.628	0.444	0.524	**0.934**	**0.922**	**0.979**	**0.943**	1	**0.987**
Total	**0.975**	**0.945**	**0.978**	**0.962**	0.652	0.530	0.642	0.454	0.530	**0.956**	**0.929**	**0.992**	**0.982**	**0.987**	1

4.3 Results

4.3.1 VMT on rural roads

A SURE model was developed in order to analyze simultaneously the effect of different factors on VMT for the four different functional classes (interstate, principal arterial, minor arterial, collector) in rural areas. Table 4.4 shows the estimation results for VMT on different functional classes of rural roads. Note that the dependent variable is the natural logarithm of VMT (log-VMT). Vehicle registrations and the amount of lane miles are likely to be endogenous in our estimation. To resolve this estimation problem, we estimated regression models to predict the amount of vehicle registrations and amount of lane miles. The predicted values were then used in the SURE model. The variables included in Table 4.4 are significant at the 90% confidence interval or higher.

Table 4.4: SURE model for VMT on rural roads

Independent Variables	**Interstate**	**Principal arterial**	**Minor arterial**	**Collector**
Constant	3.160	3.337	2.253	14.655
Percentage of White population	0.022**	0.018**	0.024**	
Percentage of Black or African-American population	0.025**	0.016**	0.021**	
Percentage of Hispanic or Latino population	0.004**			
Percentage of male population	0.017**			-0.242**
Natural logarithm of income per capita				0.852**
Percentage of population working at home (telecommuting)				-0.003**
Natural logarithm of fuel cost	-0.057*			
Natural logarithm of density		-0.082**		

Table 4.4 (Continued)

Independent Variables	Interstate	Principal arterial	Minor arterial	Collector
Natural logarithm of interstate lane miles	0.089**			
Natural logarithm of minor arterial lane miles			0.119**	0.338**
Natural logarithm of collector lane miles				0.344**
Natural logarithm of vehicle registrations	0.480**	0.713**	0.657**	
Percentage of congested miles on minor arterials				0.005**
Alabama		0.154**	0.162**	
Arizona	0.167**	-0.133**		
Arkansas	-0.092**			0.102**
California	0.173**			
Colorado		-0.059**		
Connecticut	-0.186**			0.286**
Florida		0.154**	-0.202**	
Georgia			0.109**	
Illinois		-0.229**		
Indiana				0.411**
Iowa		0.094**		0.115**
Kansas	-0.092**			
Kentucky		0.091**	-0.113**	
Louisiana		-0.167**		
Maine			0.131**	
Maryland		0.225**		
Michigan	-0.243**			
Minnesota	-0.144**			
Mississippi		0.237**	0.269**	
Missouri		0.192**		0.173**
Montana				-0.059*
Nebraska	-0.262**	-0.170**		
Nevada	0.141**			
New Hampshire				0.088**
New Jersey		0.360**		0.292**
New Mexico				-0.493**

Table 4.4 (Continued)

Independent Variables	Interstate	Principal arterial	Minor arterial	Collector
New York		-0.143**		-0.145**
North Carolina	-0.131**	0.107**		
North Dakota		0.131**		
Ohio			-0.139**	0.232**
Oregon			-0.156**	-0.092**
Pennsylvania	0.075**			
South Carolina			0.117**	
South Dakota				-0.237**
Tennessee				-0.114**
Texas		0.117**		0.431**
Utah		-0.303**	-0.286**	
Vermont		-0.142**	0.130**	0.110**
Washington		-0.050*	-0.205**	
West Virginia				0.126**
Wisconsin		0.305**	0.254**	0.352**
Wyoming			-0.143**	
Year 2000	-0.007**			-0.015**
Year 2002				0.011**
Goodness of Fit Measure (R^2)	0.848	0.852	0.857	0.901
Number of Observations	528	528	528	528

*: Variables significant at 90% level of confidence

**: Variables significant at 95% level of confidence

4.3.1.1. VMT on interstate rural roads

Table 4.4 shows the coefficients for the variables that are statistically significant in determining the VMT on interstate rural roads. According to the results, the socioeconomic factors that affect more the amount of VMT on rural interstates are race and gender and vehicle registrations, results consistent with previous studies (Greene et al., 1995; Souleyrette et al., 1995; National Energy Modeling System, 2001; Bagley and Mokhtarian, 2002; Burchel et al., 2002; McGuckin and Liss, 2005; Litman, 2005; National Surface Transportation Policy, 2007b; Browstone and Golob, 2009; Contrino and McGuckin, 2009). White, Black or African American and Hispanic or Latino people tend to travel more on rural interstates than people of other race but also men tend to travel more on rural interstates than women. The coefficients for White and Black or African American population are around 0.025 while that for Hispanic or Latino population is lower (around 0.004). Moreover, vehicle registrations (amount of vehicles) affect positively the amount of VMT more than any other factor examined in this model. Actually, a 1% increase of vehicle registration results to 0.480% increase in VMT on rural interstate.

Turning to highway capacity, a 1% increase of interstate lane miles results in a 0.089% increase of VMT on rural interstates, consistent with previous studies (Fulton et al., 2000; Noland and Cowart, 2000; Noland, 2001). However, the elasticity in that case is lower than those estimated by Fulton et al. (2000) and Noland (2001).

The only factor that results in a decrease of VMT on rural interstates is the fuel cost. As fuel cost increases, people tend to travel less, especially for personal affairs and vacation, and so the total amount of VMT on rural interstate decreases. A 1% increase of fuel cost results in a 0.057% decrease of VMT on rural interstates. This result indicates that although passenger trips are affected by fuel prices they are actually inelastic to changes of it, a result consistent with previous studies (Greene et al., 1995; Heanue, 1998; Hu et al., 2000; National Energy Modeling System, 2001; Noland, 2001; Southworth, 2001; Mabe, 2007; Congressional Budget Office, 2008; Liddle, 2009). Lastly, VMT on rural interstates varies by state and over time, as it is indicated through the different coefficients for different states and years.

4.3.1.2 VMT on principal arterial rural roads

The coefficients for the variables affecting VMT on principal arterial rural roads are shown in Table 4.4. According to the results, race, density, vehicle registrations, congestion on interstate roads and the place affect VMT on principal arterial rural roads. White and Black or African American population tend to travel more than other, a result similar to the one for rural interstates, and both coefficients are around 0.02. It is interesting that this is the only demographic characteristic that affects VMT on principal arterial and that gender, which is significant for rural interstates, is not significant in that case. Density represents the land use and it is analyzed in many different studies up to now. In this study, the increase of density (population/ square mile) results in the decrease of VMT and actually a 1% increase of it results in a 0.08% decrease of VMT, a result consistent with previous studies (Holtzclaw, 1994; Newman and Kenworthy, 1999; Barr, 2000; Kweon and Kockelman, 2004; National Surface Transportation Policy, 2007b; Chatman, 2008; Fang, 2008; Brownstone and Golob, 2009; Committee for the Study on the Relationships among Development Patterns, Vehicle Miles Traveled, and Energy Consumption, 2009). Moreover, vehicle registrations affect VMT on rural principal arterial roads as well. This factor is the most important to determine the increase or decrease of VMT as a 1% increase of vehicles leads to 0.713% increase of VMT. The amount of vehicles affects more VMT on rural principal arterial roads than VMT in any other functional class of rural roads. Last, the effect of place on VMT for rural principal arterial roads is again obvious through the different coefficients for different states.

4.3.1.3 VMT on minor arterial rural roads

Table 4.4 shows the results of the analysis for VMT on minor arterial rural roads. According to the results, the race of people affects the amount of VMT on minor arterial rural roads. White and Black or African American people travel more than other on minor arterial rural roads, a result consistent with the results for the two previous functional classes, and the coefficients for these two categories are similar and around to 0.02. Moreover, the length of network affects VMT on minor arterial rural roads, a result consistent with the one for interstates but also with previous studies (Fulton et al., 2000; Noland and Cowart, 2000; Noland, 2001). Actually, 1% increase of lane miles of minor arterial roads results in 0.119% percent increase of VMT for this functional class, elasticity which is again lower than the one estimated by Noland (2001). Also, vehicle registrations contribute significantly to the increase of VMT. This factor is again the most important in order to analyze VMT for this functional class and an increase of 1% of vehicles leads to 0.657% increase of VMT for this type of road. This result is consistent with previous studies that have indicated the influence of the amount of vehicles on VMT (Souleyrette et al., 1995; McGuckin and Liss, 2005), but also with the results for interstates and principal arterials. Last, the effect of place on VMT for rural minor arterial roads is again obvious through the different coefficients for different states.

4.3.1.4 VMT on collector rural roads

Table 4.4 shows also the result for the VMT on collector rural roads. In this case, the gender and the income per capita are the socioeconomic characteristics that affect VMT. As the percentage of male increases the amount of VMT decreases, result different than the interstate rural roads. Income per capita affects also VMT and a 1% increase results in a 0.852% increase of VMT on collector rural roads, result consistent with previous studies (Greene et al., 1995; Heanue, 1998; Fulton et al., 2000; Hu et al., 2000; National Energy Modeling System, 2001; Noland, 2001; Burchel et al., 2002; Kweon and Kockelman, 2004; Litman, 2005; McGuckin and Liss, 2005; Mabe, 2007; National Surface Transportation Policy, 2007a, 2007b; Liddle, 2009; Brazil and Purvis, 2009 ; Brownstone and Golob, 2009). The income per capita is the dominant factor affecting VMT in collector rural roads while this factor is not significant in models developed for VMT on other functional classes.

Moreover, the length of network is significant also in order to determine VMT on collector rural roads. It is interesting that the amount of lane miles of collector rural roads and also the amount of lane miles of minor arterial rural roads affect VMT. The influence of minor arterial lane miles on VMT on collector rural road indicates that the whole network should be analyzed as a system and not individually. Collector roads transfer traffic in minor arterial roads and so an increase of minor arterials lane miles is expected to attract more trips and increase VMT also on collector roads, as these roads are mainly used in order to have access on minor arterial roads. According to the results, a 1% increase of minor arterial lane miles increase VMT by 0.338% while a 1% increase of collector lane miles increase VMT by 0.344%. These results indicate that the influence of length of minor arterials and collectors on VMT on collectors is similar. Last, the place and the time affect also VMT as it is noticed through the variables for the different places and the different years.

4.3.2 VMT on urban roads

A SURE model was developed in order to analyze simultaneously the effect of different factors on VMT for the five different functional classes in urban areas. Table 4.5 shows the estimation results for VMT on different functional classes of urban roads. Note that the dependent variable is the natural logarithm of VMT (log-VMT). As was the case with the estimation of VMT on rural roads, vehicle registrations and the amount of lane miles are likely to be endogenous in our estimation. To resolve this estimation problem, we estimated regression models to predict the amount of vehicle registrations and amount of lane miles. The predicted values were then used in the SURE model. The variables included in Table 4.5 are significant at the 90% confidence interval or higher.

Table 4.5: SURE model for VMT on urban roads

Independent Variables	Interstate	Freeways	Principal arterial	Minor arterial	Collector
Constant	12.712	7.263	14.189	9.786	11.389
Percentage of urban Population	0.006^{**}	0.012^{**}	0.010^{**}	0.009^{**}	0.011^{**}
Percentage of White population		-0.067^{**}		-0.014^{**}	-0.010^{**}
Percentage of Black or African-American Population	0.005^{**}	-0.073^{**}			0.003^{*}
Percentage of Hispanic or Latino population		-0.076^{**}	0.014^{**}	-0.007^{**}	0.014^{*}
Percentage of Asian population	0.074^{**}		-0.048^{**}	0.025^{**}	
Percentage of male population	-0.108^{**}		-0.151^{**}		-0.061^{**}
Percentage of people working at home (telecommuting)		-0.004^{**}	-0.002^{**}		-0.002^{**}
Natural logarithm of fuel cost	-0.043^{**}	0.431^{**}	0.133^{**}		0.199^{**}

Table 4.5 (Continued)

Independent Variables	Interstate	Freeways	Principal arterial	Minor arterial	Collector
Natural logarithm of density				-0.015*	-0.033**
Natural logarithm of interstate lane miles	0.635**				
Natural logarithm of freeways lane miles	0.040**	0.231**			
Natural logarithm of principal arterial lane miles			0.553**		
Natural logarithm of minor arterial lane miles				0.109**	
Natural logarithm of collector lane miles					0.138**
Natural logarithm of vehicle registrations		0.871**			
Percentage of alt. fuel vehicles	-0.027*	0.338**			
Vehicles per capita			0.168**	0.078*	
Percentage of congested miles on collectors				0.001**	
Arizona	-0.109**	1.081**			
Arkansas		0.560**			
California	-0.285**		0.147**		
Colorado				-0.112**	
Connecticut			-0.499**		
Delaware			-0.359**	-0.293**	
Florida				0.211**	0.371**
Georgia	0.188**				
Illinois		-0.535**	0.103**		0.172**
Indiana			0.129**		
Kansas		0.589**			
Kentucky	0.064**	-0.175**			
Louisiana			-0.062**		
Maine			-0.130**		0.473**
Maryland		0.236**		-0.176**	
Massachusetts				0.094**	
Michigan			0.246**	0.117**	
Minnesota	0.180**			0.092**	
Mississippi				-0.374**	
Missouri	0.138**			-0.110**	
Nebraska	-0.126**				

Table 4.5 (Continued)

Independent Variables	Interstate	Freeways	Principal arterial	Minor arterial	Collector
Nevada			-0.314**	-0.177**	
New Hampshire	-0.062**		-0.233**		0.204**
New Jersey	-0.399**				
New Mexico			-0.188**		
New York	-0.446**				
North Carolina		0.519**	0.122**		
Ohio					
Oklahoma		0.644**	0.189**	0.252**	
Oregon	-0.143**			-0.142**	
Pennsylvania	-0.259**	-0.250**			0.146**
Rhode Island		0.936**	-0.231**		0.174**
South Carolina					0.337**
Texas		1.334**	-0.111**		
Utah	0.340**				
Vermont	-0.304**		-0.339**	-0.329**	
Virginia	-0.098**				
Washington			0.112**		
West Virginia		-0.627**	-0.286**		
Wisconsin	-0.208**		0.057**		-0.100**
Wyoming			0.211**		0.670**
Year 2000				0.012**	
Goodness of Fit Measure (R^2)	0.968	0.866	0.917	0.899	0.854
Number of Observations	528	528	528	528	528

*: Variables significant at 90% level of confidence

**: Variables significant at 95% level of confidence

4.3.2.1. VMT on interstate urban roads

Table 4.5 shows the results from model analyzing the VMT on urban interstate roads. The percentage of urban population affects VMT on urban interstate and as urban population increases, the amount of VMT increases. Moreover, race and gender are significant variables in determining the number of VMT in urban interstate. Black or African American and Asian people tend to travel more, while the increase of the percentage of male population results in decrease of VMT.

Turning to fuel cost the increase of it results in the decrease of VMT. Actually, increase of fuel cost by 1% results to decrease of VMT by 0.043%. The effect of fuel cost on VMT has the same magnitude for interstate roads, either rural or urban area. The length of the network is also important factor in this case and as the interstate lane miles in urban area increase by 1% the VMT increase by 0.634%. It is interesting that also the increase of freeway lane miles in urban area results also to increase of VMT in urban interstate roads. However, the influence of length of freeway lane miles is not as high as the influence of length or urban interstate lane miles (1% increase of lane miles results in increase of VMT equal to 0.040%). This result is different than the result for rural collector, where the length of minor arterial was as significant as the length of collector. Capacity of interstate is higher than freeways while capacity of minor arterial is also higher than the collector. This fact maybe is the same reason for the different results for the different functional classes that we examined here.

Furthermore, the percentage of alternative fuel vehicles affects the amount of VMT on urban interstate. The percentage of alternative fuel vehicle is used here in order to represent in which level people of each state are environmental friendly and then examines the effect of this attitude on VMT. In the case of rural interstate roads, the amount of VMT decreases as the percentage of alternative fuel vehicle increases. This result indicates that people that use alternative fuel vehicles for their trips, and so they are more environmental friendly, tend to travel less. Moreover, the range of total miles driven by an alternative fuel vehicle is limited and so that results to shorter trips and so decreased number of VMT. Last, the place is also in this case important as it is indicated by the existence of different states as significant variables in analyzing VMT.

4.3.2.2. VMT on freeways urban roads

According to Table 4.5, the percentage of urban population, the race, the new technology, the fuel cost, the length of network, the vehicle registration and the percentage of alternative fuel vehicles affect VTM on urban freeways. As the percentage of urban population increases the amount of VMT increases too while the increase of white, Black or African American and Hispanic or Latino population results in decrease of VMT, result consistent to previous studies (Contrino and McGuckin, 2009). Moreover, the increase of the percentage of people telecommuting and the increase of freeway lane miles result to increase of VMT. Actually 1% increase of freeway lane miles results in 0.231% increase of VMT. An interesting result is that the increase of fuel cost results in increase of VMT and not in decrease, as it was expected. This result could be attributed to the fact that in urban areas the trip cost is low as the trips are shorter. Moreover, the fact that the majority of trips in urban areas cannot be avoided (trips to work or school, for example) in combination with the low prices of fuel and fuel tax before 2008 may be contribute to this unexpected result. Also, the analysis of VMT on different functional classes as a system affects that results and indicates the influence of VMT on other functional classes on the examined. Last, the existence of more fuel efficient vehicles, especially for trips in the urban area has resulted to lower fuel consumption, fact that contributes to the unexpected result.

Turning to vehicles, as the vehicle registrations and also the percentage of alternative fuel vehicles increases the amount of VMT increases too. The result for the percentage of alternative fuel vehicles is different than the one for interstate, probably due to the different type of road. Freeways are usually used by people in order to get to work and they are usually shorter than interstates in urban areas. So, people can use their alternative fuel vehicles in that case as their trips are shorter and so the range of total miles driven is not a limitation. Last, the place is also important in this case.

4.3.3.3. VMT on principal arterial urban roads

According to Table 4.5, the increase of urban population results also in increase of VMT in this case while the increase of Hispanic or Latino population results to increase of VMT too. On the other side, the increase of Asian population results in decrease of VMT, result different than the one for urban interstates. The increase of male population results also to decrease of VMT on principal arterial, result consistent with the one for urban interstates. Telecommuting results to decrease of VMT as fewer trips are done by commuters while the increase of fuel cost results to increase of VMT, probably due to the same reasons as in the case of freeway VMT. It is interesting that in freeways, 1% increase of fuel cost results to 0.431% increase of VMT while in principal arterial the influence of fuel cost is not that great and 1% increase of it results to 0.133% increase of VMT. Moreover, the increase of principal arterial lane miles and the increase of vehicle per capita contribute to the increase of VMT, as expected. Last, various states are significant in the analysis of VMT on principal arterial urban roads.

4.3.3.4. VMT on minor arterial urban roads

Table 4.5 shows the results for VMT on minor arterial. The increase of urban population results to increase of VTM while the increase of density results to the decrease of

VMT, result constant with the one for VMT on rural principal arterials. Turning to race, the increase of White and Hispanic or Latino population results in decrease of VMT while the increase of Asian population has different impact on VMT, result similar with the one for urban principal arterial. As it is expected, the increase of minor arterial lane miles and the increase of vehicle per capita result both to the increase of VMT. An interesting result is that the increase of congested miles in collector results to an increase of VMT on minor arterials. This result indicates a shift of trips to different functional class roads in order to avoid congestion and reduce the travel time. Last, the place and the time affects VMT on minor arterials as well.

4.3.3.5. VMT on collector urban roads

Table 4.5 shows also the results from the analysis of VMT on collector urban roads. The percentage of urban population and the density affect VMT in collector and the magnitude of this effect is similar with the other functional roads analysis. Moreover, the increase of White population results to decrease of VMT, result constant with the previous results for the other functional classes, while the increase of Black or African American and Asian population has a different effect. It is interesting that the increase of fuel cost and fuel tax results to increase of VMT. Fuel cost has the same effect also on VMT on urban freeways and urban principal arterials and the reasons for this result are common among the different functional classes. Increase of telecommuting results to decrease of VMT on collectors while increase of collector lane mile result, as it was expected, to increase of VMT. Last, the place is significant in this case as well.

4.3.3 Total VMT

Table 4.6 shows the results of the analysis of total VMT. A random coefficients panel data model was developed to estimate total VMT. As was the case with the SURE models, vehicle registrations and the amount of lane miles were exogenously predicted. The predicted values were then used in the panel data model. All the variables included in Table 4.6 are significant at the 90% confidence interval or higher.

Table 4.6: Random Coefficients-Panel Data model for total VMT

Independent Variables	**Coefficient**	
Non Random Parameters		
Natural logarithm of fuel cost	-0.014**	
Natural logarithm of fuel tax-State	-0.037**	
Natural logarithm of vehicle registrations	0.052**	
Percentage of alternative fuel vehicles	0.016**	
Natural logarithm of total rural lane miles	0.068**	
Natural logarithm of total urban lane miles	0.256**	
Random Parameters		
	Mean	**Standard deviation**
Constant	4.616**	0.015
Natural logarithm of population	0.647**	0.004
Percentage of urban population	0.0003**	0.0002
Percentage of White population	-0.002**	0.0001
Percentage of Hispanic or Latino population	-0.005**	0.005
Percentage of Asian population	0.004**	0.003
Natural logarithm of income per capita	0.067*	0.0004
Natural logarithm of density	-0.009**	0.002
Goodness of Fit Measure (R^2)	0.991	
Number of Observations	528	

*: Variables significant at 90% level of confidence

**: Variables significant at 95% level of confidence

Table 4.6 shows the results from the estimation of total VMT. Fuel cost, fuel tax, vehicle registration, percentage of alternative fuel vehicles and length of network (rural and urban lane miles) are the variables of which the parameter is constant and not normally distributed. Increase of fuel cost and fuel tax would result to a decrease of VMT. The increase of fuel cost and fuel tax results to increase of trip cost that affects directly travel demand and results to decrease of it, according also to previous studies (Greene et al., 1995; Heanue, 1998; Hu et al., 2000; National Energy Modeling System, 2001; Noland, 2001; Southworth, 2001; Mabe, 2007; Congressional Budget Office, 2008; Liddle, 2009). The fuel tax is examined separately from the fuel cost as it is controlled only by state governments, while the fuel cost can be affected by other factors as well. According to Table 4.6, a 1% increase of fuel cost results in a 0.014% decrease of VMT while a 1% increase of fuel tax results in a 0.037% decrease of VMT. It is interesting that the effect of fuel tax is higher than the effect of fuel cost. Turning to the effect of vehicles on VMT, the increase of vehicle registrations but also the increase of percentage of alternative fuel vehicles result to an increase of VMT. Interestingly, while a 1% increase of vehicle registration results in a 0.052% increase of VMT, the effect of alternative fuel vehicles is lower and a 1% increase of their percentage results in an only 0.016% increase of VMT. Lastly, the length of the network also affects, as it is expected and noticed in previous studies (Fulton et al., 2000, Noland and Cowart, 2000; Noland, 2001), the travel demand. A 1% increase of rural lane miles results to 0.068% increase of VMT while the effect of urban lane miles is much higher and a 1% increase of them results to a 0.256% increase of VMT. It is interesting that the amount of urban lane miles affects travel demand more than the amount of rural lane miles, probably due to the higher amount of people affected by road network supply in urban areas and the higher amount of trips that can be induced in those areas, compared to rural areas.

Turning to random parameters, demographic and socioeconomic factors but also density are those factors the parameters of which are normally distributed. Population is the dominant factor affecting VMT. The parameter for population is normally distributed with mean equal to 0.647 and standard deviation 0.004. Given these estimates, the parameter ranges from 0.635 up to 0.659, and so population positively affects VMT. Turning to urban population, the coefficient of this variable is less than zero for 68% of the cases, as the mean of it is 0.0003 and the standard deviation is 0.0002. According to that result, the probability of an increase in VMT due to an increase in urban population is equal to the probability of a decrease in VMT due to the same increase. The different effect of urban population on VMT represents the specific characteristics of each area and how those affect VMT. For example, the effect of increase of urban population in Iowa on travel patterns is different than that in California due to different weather conditions but also due to other characteristics, such as availability of transit and residents' attitudes.

Similar factors could also affect the coefficient estimated for density. The mean of that coefficient is equal to -0.009 and the standard deviation is 0.002. Although the effect of density on VMT varies and ranges from -0.015 up to -0.003, probably due to different characteristics for different areas in the U.S., the effect on VMT remains negative for the 99.7% of the data. Race is another demographic characteristic that affects travel demand and that its parameter is normally distributed. According to Table 4.6, the coefficient for the percentage of White population ranges from -0.0023 up to -0.0017 and so the increase of White population results in decrease of VMT in the majority of cases. The increase of

Hispanic or Latino and the Asian population has not always the same impact on the amount of total VMT, as it can be concluded from the results for the mean and the standard deviation of their coefficients. The coefficient for Hispanic or Latino population is less than zero for 66% of the cases while the coefficient for Asian population is less than zero for the 5% of the cases. Income per capita is the last socioeconomic factor with a normally distributed parameter. The mean of the coefficient is equal to 0.067 and the standard deviation is equal to 0.0004. This result indicates that increased income per capita would mostly result in an increase in travel demand with a coefficient that ranges from 0.0658 up to 0.0682. The different influence of income per capita on VMT across different areas can be probably attributed to the different cost of living across areas but also by other factors, such as lifestyle, availability of transit and development of the area.

CHAPTER 5 SCENARIO-BASED ESTIMATION OF ENERGY CONSUMPTION IN THE FUTURE

5.1 Traffic demand measures, innovations in transportation and government policy

As passenger transportation on highways increases, new measures and policies need to be established in order to reduce the rate of increase and encourage passengers to shift from highway modes to other modes of transportation. Various policies have been discussed and examined during the last years in order to manage travel demand and reduce energy consumption and greenhouse gas emissions. The expansion of the intercity high speed rail in order to serve more areas, policies promoting the use of alternative fuel vehicles, the increase of fuel tax/ fuel cost and the development of new land use patterns are among the policies that have been discussed during the last years. This Chapter discusses the effect of those policies on VMT, energy consumption and greenhouse gas emissions, according to different scenarios for each policy.

5.1.1 Intercity High Speed Passenger Rail

Passenger rail consists of one of the major mode of transportation for intercity trips worldwide. However, the use of passenger rail in the US is limited and not comparable to that in Japan and Europe. Various reasons have contributed to the limited use of passenger rail in the US, such as the preference of people to drive their own vehicle and the development of the highway system such that it is much higher than the development of the passenger rail. The only High Speed Rail Corridor in the US is the Northeast Rail Corridor, connecting Washington D.C. with Boston, Massachusetts through New York. The passenger rail in this corridor provides a competitive alternative to the car but also to the airplane as it provides reduced travel time and increased comfort between the major cities at the East Coast. The impact that the Northeast Rail Corridor has on passenger transportation by car is examined.

Various studies have determined either the influence of the Northeast Rail Corridor on passenger transportation in the specific area or the increase and/or the success of the high speed rail, analyzing the change of ridership from one year to another. However, those studies did not examine the market share and the influence of passenger rail on VMT and passenger trips. In this study, the influence of high speed rail on transportation mode market share and more specifically on the percentage of people who diverted or tend to divert from car and highway travel to trips by rail is of interest. For that reason, only studies that focus on the amount of people who would shift from highway travel to rail are considered.

A study prepared for the Chicago- St. Louis corridor (TranSystems, 2010)) estimated the shift from automobiles to rail to be equal to 13.3%, or within arrange from 6.6% (low) to 19.9% (high). As it is noted in the study, the shift of automobile trips to rail is very challenging to estimate as traveling by car includes various purposes and various destinations.

In California, the high speed rail corridor connecting San Francisco Bay Area and Los Angeles Metropolitan Area is estimated to influence the transportation mode market share and results in the following market shares for the three modes: air 26%, high speed rail 45% and automobile 29% (California High-Speed Rail Authority, 2010). This effect of high speed rail on automobile trips is anticipated and may be attributed to the different characteristics of trips (such as shorter distances, congested network) but also due to other state-specific characteristics (such as weather conditions, people's attitude towards to air pollution).

5.1.2 Alternative fuel vehicles

Alternative fuel vehicles are considered as the solution to the increased demand for energy. The adoption of alternative fuel vehicles compared to conventional vehicles would result to lower energy demand and petroleum use. As it was shown in Table 4.6, the use of alternative fuel vehicles would result to an increase of total VMT, but this increase is lower than the increase caused by the total amount of vehicles (expressed as the number of registrations). This is likely attributed to the limited range of driven VMT by alternative fuel vehicles (PHEV have a travel range of 40 miles, for example) but also to the increased inherent concern of people who own alternative fuel vehicles about the environment that might influence the amount of trips they make by personal vehicle.

Policies that would result to a higher market penetration of alternative fuel vehicles would have direct effects on energy consumption.

5.1.3 Government's policy towards fuel cost/fuel taxes

There is an ongoing debate on increasing fuel tax, in order to raise revenues for new construction. Fuel cost and fuel tax are two factors affecting total VMT (shown in table 4.6); increase in both factors would result to a decrease in the total amount of VMT. The increased fuel cost and the increased fuel tax increase the trip cost and so directly result to reduced travel demand. The increase of fuel tax in order to account for inflation (eg. of government policy) would result directly to increase of trip cost that affects travel demand, according to results shown in chapter 4 but also in previous studies (Greene et al., 1995; Heanue, 1998; Hu et al., 2000; National Energy Modeling System, 2001; Noland, 2001; Southworth, 2001; Mabe, 2007; Congressional Budget Office, 2008; Liddle, 2009).

5.1.4 New planning patterns/ increase of density

Density and the type of development affect the amount of trips and VMT. According to Table 4.6, VMT are lower in higher density areas (elasticity of -0.009); double density results to 0.9% decrease of total passenger trips in U.S., equal to 20 million VMT. Land use policies that would encourage the development of more dense areas would affect directly the amount of VMT and would result to a decrease in VMT and energy consumption. As it is indicated in Holtzclaw (1994), double density results to 20-25% less driving per family, while Fang (2008) estimated that a 25% increase in density results to a reduction in the miles driven per household by 64.6 miles. The increase of density results to fewer trips with cars as people can either walk or use other modes (bicycling, transit) for their trips. Moreover, the increased density reduces the length of each trip and so results to reduce of VMT but also reduce of energy consumption and greenhouse gas emissions.

5.2 Scenario-based Estimation of VMT, Energy Consumption, and Greenhouse Gas Emissions in 2040

5.2.1 VISION- Annual VMT Growth Factors

The effect of the policies or new technologies that were presented in Section 5.1 on VMT, energy consumption and greenhouse gas (GHG) emissions is examined based on different scenarios and with a use of a software package. Various software packages have been developed by national labs in order to estimate the energy needs according to the amount of trips in the future. One of the most widely used software packages to date is VISION, which was developed by the Argonne National Laboratory for the U.S. Department of Energy (Singh et al., 2003; Ward, 2008). VISION estimates the energy consumption in the horizon year according to the amount of VMT and the percentage of alternative fuel vehicles in the base year, as well as predictions of the amount of VMT and the percentage of alternative fuel vehicles for years between the base and the horizon year.

The horizon year selected for this study is 2040. In order to predict VMT in the horizon year, a growth factor is applied on the VMT for the base year (2008). The growth factor between 2008 and 2040 is estimated as the average of the growth factors for the following periods: 1998-2003 (1.0153 or 1.53% increase per year) and 2003-2008 (1.004 or 0.4% increase per year). Table 5.1 shows the estimates of total VMT and the annual VMT growth factor for each time period (1998-2003, 2003-2008, 2008-2040). The estimated annual VMT growth factor for the period 2008-2040 is 1.0097 (or 0.97% increase per year). It can be observed that the total VMT increased at a lower rate during the time period 2003-2008 compared to the time period 1998-2003.

Table 5.1: Growth factors for total VMT

Year	Annual VMT Growth Factor	Total VMT (trillions)
2003	1.0153	2.175
2008	1.004	2.227
2040	1.0097	2.919

Note that the annual VMT growth factors can also be estimated using the developed models (presented Chapter 4) and by applying growth factors for the independent variables that are included in the models.

5.2.2 Scenario 1: Expanded passenger rail network

Under this scenario, the influence of an extended passenger rail network on passenger trips by personal car is examined. The existence of reliable and competitive passenger rail would encourage people to use it, resulting in a decrease of trips by personal vehicles and as a result to a decrease in the total amount of VMT. The shift of passengers from personal vehicles to rail depends on the characteristics of their trips but also on the characteristics of the network and the existence of other modes (transit) supporting the use of high speed rail. These characteristics vary from state to state. In order to account for these characteristics and the differences across transportation systems (mature versus developing), an average percentage of people shifting from personal vehicle trips to high speed rail is assumed based on the studies presented in Section 5.1.1.

For the purpose of this study, it is assumed that an extended intercity passenger rail network in the U.S. would reduce long-distance passenger trips (more than 50 miles) by personal vehicles by 15%. In order to estimate the influence of high speed passenger rail on energy consumption and GHG emissions, using the software VISION, it is necessary to modify the growth factor for total VMT for the time period 2008-2040 (Table 5.1). According to the National Household Survey 2001, long-distance trips consist of 25% of total trips in the U.S. As such, a 15% reduction of the long trips would result to a 0.25*0.15=0.0375 or 3.75% reduction of total VMT. In that case, the new growth factor will be (1-0.0375)*1.0097=0.972. This modified growth factor was used as an input in VISION.

Note that this modified growth factor is used only for the years 2037–2040. For the time period between 2008 and 2037, the growth factors increase gradually up to the value that is estimated for 2040, in order to account for the gradual market penetration of passenger high speed rail in the future. Table 5.2 shows the effect of high speed rail on energy consumption and greenhouse gas emissions in 2040.

Table 5.2: Effect of high speed rail on energy consumption and GHG emissions

Influence of high speed rail	Annual VMT growth factor	Energy consumption (%reduction)	Greenhouse gas emissions (% reduction)
		*Light Duty Vehicles**	
-3.75%	0.972	63.4%	63.7%
		Cars	
		45.0%	45.1%

*include cars and light trucks (vans, pickups and sport utility vehicles).

Considering a 15% reduction of VMT due to the development of high speed rail network and the shift of trips from highway to rail, the energy consumption and the greenhouse gas emissions for light duty vehicles (passenger cars and light trucks) would decrease by around 63% due to the high reduction of VMT. In the case of cars, the total estimated reduction of energy consumption and greenhouse gas emissions is around 45%, much lower than the total reduction for light duty vehicles, as anticipated. Moreover, the increased number of sport utility vehicles (SUVs) and vans that are used as personal vehicles during the last decade has increased the number of light trucks compared to cars.

5.2.3 Scenario 2: Higher number of alternative fuel vehicles

The effect of alternative fuel vehicles on energy consumption and greenhouse gas emissions is considered as following by consuming less energy and emitting less. In order to estimate energy consumption and GHG emissions, two different scenarios are examined: a realistic (low) scenario; and an aggressive (high) scenario. Both scenarios are based on predictions of the market share of alternative fuel vehicles in the future (Electric Power Research Institute, 2007; Hadley and Tsvetkova, 2008; Fulton, 2009) and are shown in Table 5.3. The realistic scenario corresponds to a low market penetration of alternative fuel vehicles by 2040. The aggressive scenario consists of higher predictions of market share for the alternative fuel vehicles (as a result of federal incentives or increased environmental awareness of consumers). The analysis of these two scenarios helps determine a range of potential reduction in energy consumption and emissions due to scenarios of market penetration of alternative fuel vehicles.

Table 5.3: Distribution of vehicles for base year and horizontal year (realistic and aggressive scenario)

	Base Year	*Realistic Scenario*	*Aggressive Scenario*
	Distribution by vehicle type		
Conventional	89.83%	16.00%	1.98%
PHEV	0.00%	24.00%	29.00%
HEV	4.09%	13.00%	14.00%
Diesel	1.20%	6.50%	1.00%
E-85 Ethanol	4.85%	9.50%	10.50%
Diesel HEV	0.01%	3.58%	5.00%
Diesel PHEV	0.00%	8.00%	12.00%
Fuel Cell	0.00%	10.00%	13.50%
EV	0.00%	9.40%	13.00%
CNG	0.02%	0.02%	0.02%

According to Table 4.6, the elasticity of VMT with respect to the percentage of alternative fuel vehicles is equal to 0.016. A 68.53% increase of the percentage of alternative fuel vehicle would result to a 1.096% increase in VMT (realistic scenario) while a 88.05% increase of the percentage of alternative fuel vehicles would result to 1.408% increase of VMT (aggressive scenario). The increase of the percentage of alternative fuel vehicles for each scenario is calculated as the difference between the percentage of alternative fuel vehicles in the future (77.5% in the realistic scenario and 97.02% in the aggressive scenario) and the percentage of alternative fuel vehicles now (8.97%) The adjusted growth VMT factors would be in those cases: (1+0.01096)*1.0097=1.0208 (realistic scenario) and (1+0.01408)*1.0097=1.0239. These modified growth factors were used as an input in VISION. Note that these modified growth factors are used for the years 2039–2040, as it is assumed that only during the last two years (2039,2040) the percentage of alternative fuel vehicles would be equal to the one estimated, based on the studies for the market share. For the years 2008-2010, the estimated growth factor, shown in Table 5.1, is applied, while for the years 2010-2038 the growth factors increase gradually up to the value that is estimated for 2040, in order to account for the gradual market penetration of alternative fuel vehicles in the future. The estimation results of reduction of energy consumption, carbon and greenhouse emissions under each scenario in 2040, based on the distributions of vehicles presented in Table 5.3., are shown in Table 5.4.

Table 5.4: Effect of alternative fuel vehicles on energy consumption and GHG emissions

Influence of alternative fuel vehicles (0.016)	Annual VMT growth factor	Energy consumption (%reduction)	Greenhouse gas emissions (% reduction)

Table 5.4 (Continued)

Influence of alternative fuel vehicles (0.016)	Annual VMT growth factor	Energy consumption (%reduction)	Greenhouse gas emissions (% reduction)
Realistic Scenario			
		Light Duty Vehicles	
1.096	1.0208	22.1%	11.0%
		Cars	
		-8.4%	-29.8%
Aggressive Scenario			
		Light Duty Vehicles	
1.408	1.0239	30.5%	17.5%
		Cars	
		2.6%	-21.7%

The reduction in energy consumption due to the different distribution of vehicles ranges from 22.1% up to 30.5% while the reduction in greenhouse gas emissions ranges from 11.0% up to 17.5% for light duty vehicles. The reduction of energy consumption is much lower for cars while an increase of greenhouse gas emissions is observed in the case of cars, probably due to the increase of total VMT.

5.2.4 Scenario 3: Higher fuel tax

Fuel tax consists of another aspect of trip cost that affects VMT and can be changed through policies. The effect of a policy that would increase fuel tax in order to take into account for the inflation would be examined in order to determine its influence on energy consumption and greenhouse gas emissions. Fuel tax has remained constant through 1998 and the average tax is equal to 20.85 cents per gallon. However, the value of money today is not equal to the value of money in 1998 and an adjustment of fuel tax for inflation should be implemented. If this is pursued, then the resulting fuel tax rate is 27.42 cents per gallon, which corresponds to a 31.5% increase of fuel tax. According to Table 4.6, the elasticity of VMT with respect to the fuel tax is equal to -0.037. So, a 31.5% increase of fuel tax would result to a 1.2% decrease in VMT. The adjusted growth VMT factor would be in that case: (1-0.012)*1.0097=0.997. This modified growth factor was used as an input in VISION. Note that this modified growth factor is used for the years 2011–2040, as it is assumed that this policy would be implemented starting in year 2011. For the years 2008-2010, the estimated growth factor, shown in Table 5.1, is applied. Table 5.5 shows the reduction of energy consumption and greenhouse gas emissions due to this scenario.

Table 5.5: Effect of increased fuel tax on energy consumption and GHG emissions

Influence of fuel tax (-0.037)	Annual VMT growth factor	Energy consumption (%reduction)	Greenhouse gas emissions (% reduction)
-1.2%	0.997	*Light Duty Vehicles*	
		51.1%	51.5%
		Cars	
		26.6%	26.6%

The increase of fuel tax in order to account the inflation would result to 1.2% decrease of VMT and to around 51% decrease of energy consumption and greenhouse gas emissions for light duty vehicles and 26.6% decrease of energy consumption and greenhouse gas emissions for cars.

5.2.5 Scenario 4: Higher density

The effect of a policy that would encourage the development of more dense areas in US on travel demand, energy consumption and greenhouse gas emissions is examined under this scenario. Table 4.6 showed that a 1% increase of density results to a 0.009% decrease of VMT. For the purpose of this study, the effect of doubling the density (a 100% increase) on energy consumption and greenhouse gas emissions is examined. A 100% increase of density would result to a 0.9% decrease of VMT and so the VMT growth factor would be in that case:

(1-0.009)*1.0097=1.0006. This modified growth factor was used as an input in VISION. Note that this modified growth factor is used only for the years 2015–2040. For the time period between 2008 and 2014, the estimated growth factor, shown in Table 5.1, is applied. Table 5.6 shows the influence of increased density on VMT but also on energy consumption and greenhouse gas emissions.

Table 5.6: Influence of increased density on energy consumption and GHG emissions

Influence of density (elasticity of-0.009)	Annual VMT growth factor	Energy consumption (%reduction)	Greenhouse gas emissions (% reduction)
-0.9%	1.0006	*Light Duty Vehicles*	
		43.3%	43.8%
		Cars	
		14.9%	15.0%

The results show that a 100% increase of density (double density) would result to a 0.9% reduction of VMT, a 43.3% reduction of energy consumption and 43.8% reduction of greenhouse gas emissions for light duty vehicles. The reduction of those measures is much lower for cars, result consistent with the results found in the previous scenarios.

CHAPTER 6 CONCLUSIONS

This study presented the results of the analysis of VMT in U.S. Aim of the study was the estimation of impact of various factors on passenger trips. Demographic and socioeconomic factors but also the trip cost and the length of network are among the factors analyzed in this study.

This thesis investigated the effect of demographic and socioeconomic characteristics, land use, road capacity, and fuel prices on VMT in a multivariate context. Moreover, this thesis examined the influence of new technology (such as telecommuting and alternative fuel vehicles) on VMT and passenger trips. Using panel data for the 48 continental states during the period 1998-2008, simultaneous equation models for predicting VMT on different road functional classes and examining how changes in policies and technology could affect passenger trips across the nation. The methodology of random parameters panel data models was applied to estimate total VMT in the US. To assess the influence of each significant factor on VMT, elasticities were estimated.

The second objective of this thesis was to predict energy demand and greenhouse gas emissions in the future based on the results of travel demand (VMT) estimation and four scenarios. The scenarios represent different policies in the future, such as the development of intercity high speed rail, the increase of fuel tax, the increase of alternative fuel vehicles and the increase of density. The software VISION, developed by Argonne Laboratory, was used for the estimation of the energy consumption and greenhouse gas emissions under each scenario. The estimated models of passenger trips can assist transportation planners and policy-makers to determine the energy and transportation infrastructure investment needs in the future.

6.1 Travel Demand

Three different models were developed in order to estimate the effect of various factors on travel demand. SURE methodology was used in order to estimate the travel demand across different functional classes of rural and urban roads, while in the case of total VMT, panel data and random parameters were used for that analysis. The use of panel data was selected in order to estimate the effect of place (state) and time (year) on travel demand and eliminate the correlation among those factors.

6.1.1 SURE models for rural and urban roads

The main findings of this analysis are summarized as follows:

- Gender, race, percentage of urban population, income per capita and vehicle registrations are the demographic and socioeconomic characteristics that affect travel demand in rural and urban roads, result consistent with previous studies (Greene et al., 1995; Heanue, 1998; Souleyrette et al., 1995; Fulton et al., 2000; Hu et al., 2000; National Energy Modeling System, 2001; Noland, 2001; Bagley and Mokhtarian, 2002; Burchel et al., 2002; Kweon and Kockelman, 2004; McGuckin and Liss, 2005; Litman, 2005; Mabe, 2007; National Surface Transportation Policy, 2007a, 2007b; Brazil and Purvis, 2009 ; Browstone and Golob, 2009; Contrino and McGuckin, 2009; Liddle, 2009).
- Higher fuel cost would decrease travel demand on rural and urban interstates but VMT are actually inelastic to those changes, result consistent with previous studies (Greene et al., 1995; Heanue, 1998; Hu et al., 2000; National Energy Modeling System, 2001; Noland, 2001; Southworth, 2001; Mabe, 2007; Congressional Budget

Office, 2008; Liddle, 2009). The effect of fuel cost varies across functional classes of urban roads.

- An increase in the number of people working at home (telecommuting) would decrease VMT while the increase of alternative fuel vehicles would decrease VMT on interstates but increase VMT on urban freeways.
- Turning to highway capacity, the number of lane miles per functional class affects VMT on the majority of functional classes, result also found in previous studies (Fulton et al., 2000; Noland and Cowart, 2000; Noland, 2001). Other notable results include the lower values of elasticities of VMT with respect to the number of lane miles, compared to previous studies, and the values of cross-elasticities with respect to the lane miles across different functional classes (range from 0.04 up to 0.338). The cross-elasticity of VMT on minor arterials with respect to the level of congestion on urban collectors and theVMT was found significant and equal to 0.001
- Higher density would result to a decrease in VMT, result consistent with previous studies (Holtzclaw, 1994; Newman and Kenworthy, 1999; Barr, 2000; Kweon and Kockelman, 2004; National Surface Transportation Policy, 2007b; Chatman, 2008; Fang, 2008; Committee for the Study on the Relationships among Development Patterns, Vehicle Miles Traveled, and Energy Consumption, 2009; Browstone and Golob, 2009).
- Overall, VMT vary across the states and analysis years.

6.1.2 Panel Data for total VMT

Population, percentage of urban population, gender, income per capita and vehicle registrations are the demographic and socioeconomic factors that affect total VMT in the U.S. These results are consistent with those for rural and urban roads. In addition, the analysis revealed that the parameters for population, percentage of urban population, gender and income per capita are normally distributed and vary across passengers and states. Another factor that influence total VMT and has a normally distributed coefficient is density.

Turning to factors with constant coefficient, the trip cost, including fuel cost and fuel tax, negatively affect total VMT. The effect on VMT due to the increased percentage of alternative fuel vehicles is positive, yet lower than that due to the total amount of vehicles. Last highway capacity and in specific, the lane miles on rural and urban roads affect total VMT. The influence of urban lane miles is much higher than the influence of rural lane miles, probably due to the higher amount of people that are affected in the case of increased capacity on urban areas.

6.2 Energy consumption and greenhouse gas emissions

Energy consumption by passenger transportation consists one of the largest components of energy consumption by the transportation sector and almost 12% of the total energy consumption in the United States. As energy and availability of energy resources have become major global challenges, the prediction of future energy needs and the reduction of energy consumption are of increasing importance. Different scenarios, representing various policies, were examined in order to determine the effect of those policies on travel demand (total VMT) and energy consumption.

It was estimated that the expansion of the intercity passenger rail network would have the largest effect on energy consumption and greenhouse gas emissions, while the increase of alternative fuel vehicles would have the lowest impact. In specific, the expansion of intercity high speed rail would result to a 63.4% reduction in energy consumption for light duty vehicles while the increase of alternative fuel vehicles would result to a 30.5% reduction in energy consumption (aggressive scenario) for light duty vehicles. The expansion of a high speed rail network would not result to a decrease in passenger trips but to the shift of these trips to another mode (rail). This policy would be the most beneficial as it would result to the greatest energy consumption without actually reducing the total number of passenger trips. Moreover, the increase of fuel tax by 31.5% would result to a 51.1% decrease in energy consumption, while doubling density would result to a 43.3% reduction in energy consumption for light duty vehicles. The increase of fuel tax can be considered as a profitable policy, as it would result to decrease in energy consumption by reducing VMT and could probably result in an increase in revenues for new highway improvements.

6.3 Limitations of this Thesis

The limitations of this thesis are summarized as follows:

- Data limitations: Growth factors were applied to estimate the demographic and socioeconomic variables for the years between 1990-2000 and 2000-2008, when data were not available.
- Assumptions: The results for the energy consumption and the greenhouse gas emissions in 2040 are based on assumptions about the estimated growth factors for VMT, as well as the estimates of recent studies on the market share of alternative fuel

vehicles and the effect of high speed rail on future trips. These estimates need to be updated as more information becomes available.

- Software: The software VISION, which was used for the estimation of energy consumption and greenhouse gas emissions in the future, does not allow the user to modify the default values of VMT but only modify the growth factors. As such, the effect of various scenarios on VMT and energy demand was determined only through the modification of the annual VMT growth factor.

6.4 Recommendations for Future Research

Future research using updated data on the demographic and socioeconomic factors but also on the distribution of vehicles in the future would provide improved and more reliable results. Moreover, further research is needed in order to investigate the impact of the proposed policies on VMT and energy consumption. A more detailed analysis of mode choice for passenger trips would result to more accurate estimation of ridership on high speed rail and as such to improved results about the impact of high speed rail on energy consumption. The mode choice analysis but also a better knowledge of market share in the future would also result to better estimates of the impact of alternative fuel vehicles on energy consumption. Last, future research on freight transportation and in particular, the investigation of the factors that affect freight trips would enable the estimation of interdependencies between freight and passenger transportation and result to a better understanding of transportation system as a whole.

Finally, this research could be useful to transportation planners and decision makers as it provides prediction models for VMT in the future and estimates of the impact of the factors that affect VMT. Moreover, this research presented a methodology on how to examine the influence of various policies on VMT that transportation planners and decision makers can use in order to investigate the impact of proposed future policies or technology innovations.

BIBLIOGRAPHY

American Community Survey 2006-2008, U.S. Census Bureau. http://factfinder.census.gov/home/saff/main.html?_lang=en.

Bagley, M.N., and P.L. Mokhtarian. (2002). The impact of residential neighborhood type on travel behavior: a structural equation modeling approach. *The Annals of Regional Science*, **36** (2), 279–297.

Baltagi, B. (1994). *Econometric Analysis of Panel Data*. John Wiley & Sons, Ltd, Chichester, West Sussex, UK, 1994.

Barr, L.(2000). Testing for the significance of Induced Highway Travel Demand in Metropolitan Areas. *Transportation Research Record*, 1706, 4-8.

Biorn, E, Lindquist, K and T. Skjerpen (1998). Random Coefficients and Unbalanced Panels: An Application on Data from Norwegian Chemical Plants. Discussion Paper No 235, Statistics Norway, research Department. http://www.ssb.no.

Boarnet, M., and R. Crane (2001). The influence of land use on travel behavior: specification and estimation strategies. *Transportation Research*, Part A (35), 823-845.

Brazil, H. and C. Purvis (2009). BASSTEGG - Sketch Planning Charrette/GIS Models for Predicting Household Vehicle Miles of Travel (VMT) and Greenhouse Gas (CO_2) Emissions.

Metropolitan Transportation Commission TRB 2009 Transportation Planning, Land Use, and Air Quality Conference July 29, 2009 Centennial, Colorado.

Brownstone, D. and T. Golob (2009). The impact of residential density on vehicle usage and energy consumption. *Journal of Urban Economics*, 65, 91-98.

Burchell, R., G. Lowenstein, W. R. Dolphin, C. C. Galley, A. Downs, S. Seskin, K. G. Still, and T. Moore (2002). Cost of Sprawl—2000. *Transit Cooperative Research Program Report 74.* Transportation Research Board, National Research Council, Washington, D.C.

California High-Speed Rail Authority. 2008-2010 State of California. http://www.cahighspeedrail.ca.gov/

CENSUS 1990. U.S. Census Bureau. Summary Tape File 1 (STF 1). http://www.census.gov/main/www/cen1990.html.

CENSUS 2000. U.S. Census Bureau. Summary File 1 (SF 1) and Summary File 3 (SF 3) http://factfinder.census.gov/home/saff/main.html?_lang=en.

Cervero, R., and M. Duncan (2006). Which Reduce Vehicle Travel More: Jobs-Housing Balance or Retail-Housing Mixing? *Journal of the American Planning Association*, 72 (4), 475-490.

Chatman, D. (2008). Deconstructing development density: Quality, quantity and price effects on household non-work travel. *Transportation Research*, A (42), 1008-1030.

Chicago to St. Louis. 220 mph High Speed Rail Alternative Corridor Study. Volume 2-Ridership and Benefits (2010). Prepared by TranSystems. Chicago, IL.

Committee for the Study on the Relationships Among Development Patterns, Vehicle Miles Traveled, and Energy Consumption Driving and the Built Environment. The effects of Compact Development on Motorized Travel, Energy Use and CO_2 Emissions. Transportation Research Board, Board on Energy and Environmental Systems, Washington D.C., 2009.

Congressional Budget Office. 2008a. (2008).Effects of Gasoline Prices on Driving Behavior and Vehicle Markets. Congress of the United States, Washington, D.C.

Congressional Budget Office. 2008b. (2008). Climate-Change Policy and CO2 Emissions from Passenger Vehicles. Economic and Budget Issue Brief. Congress of the United States, Washington, D.C.

Contrino H., and N. McGuckin (2009). Travel Demand in the Context of Growing Diversity. *TR News*, 264, 4-9.

Electric Power Research Institute (2007). *Environmental Assessment of Plug-In Hybrid Electric Vehicles*. Electric Power Research Institute, Palo Alto, CA.

Energy Information Administration. Historical Data: Alternative Transportation Fuels (ATF) and Alternative Fueled Vehicles (AFV). Table V-3. U.S Department of Energy. http://www.eia.doe.gov/cneaf/alternate/page/atftables/afv_hist_data.html.

Ewing, R., K. Bartholomew, S. Winkelman, J. Walters, and D. Chen (2007) . *Growing Cooler: The Evidence on Urban Development and Climate Change*. Urban Land Institute, Washington, D.C.

Fang, H. (2008). A discrete–continuous model of households' vehicle choice and usage, with an application to the effects of residential density. *Transportation Research*, B (42), 736-758.

Fulton, L., B. Noland, D. Meszler, and J. Thomas. (2000). A Statistical Analysis of Induced Travel Effects in the U.S. Mid-Atlantic Region. *Journal of Transportation and Statistics*, 3(1), 1-14.

Fulton, L. (2009). *Transport, Energy and CO_2: Moving Toward Sustainability. International Energy Agency*. Global auto makers event at COP 15, Copenhagen, Denmark, 14 December 2009.

Greene D, S. Chin, and R. Gibson. (1995). Aggregate Vehicle Travel Forecasting Model, Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Hadley, S., and A. Tesvetkova (2008). *Potential Impacts of Plug-in Hybrid Electric Vehicles on Regional Power Generation*. Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Heanue, K. (1997). Transportation Research Circular 481: Highway Capacity and Induced Travel: Evidence and Implications. TRB, National Research Council, Washington D.C., 33-45.

Highway Performance Monitoring System (HPMS). Federal Highway Administration (FHWA). http://www.fhwa.dot.gov/policy/ohpi/hpms/index.cfm.

Highway Statistics. Tables HM-20, VM-2, MV-1, MF-121T, MF-205, MF-5, HM-42. Federal Highway Administration (FHWA). http://www.fhwa.dot.gov/policy/ohpi/hss/index.cfm.

Holtzclaw, J. (1994). Using Residential Patterns and Transit to Decrease Auto Dependence and Costs. National Resources Defense Council, Sierra Club, San Francisco.

Hsiao, C.(1986). *Analysis of Panel Data.* Cambridge University Press, Cambridge, UK.

Hsiao, C. and M. H. Pesaran (2004).Random Coefficient Panel Data Models. CESifo Working Paper No 1233, July 2004. www.CESifo.de.

Hu, P., D. Jones, T. Reuscher, R. Schmoyer, and L. Truett. (2000) Projecting Fatalities in Crashes Involving Older Drivers, 2000–2025. Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Krizek, K. J. (2003). Residential Relocation and Changes in Urban Travel: Does Neighborhood-Scale Urban Form Matter? *Journal of the American Planning Association*, 69 (3), 265–279.

Kweon, Y., and K. Kockelman. (2004). Nonparametric Regression Estimation of Household VMT. Submitted for presentation and publication at the 2004 Annual Meeting of Transportation Research Board.

Liddle, B. (2009). Long-run relationship among transport demand, income, and gasoline price for the US. *Transportation Research*, Part D (14), 73-82.

Litman, T. (2005). The Future Isn't what it used to be. Changing Trends and their implications for Transport Planning, Victoria Transport Policy Institute.

Mabe, K. (2007). Impact of Gas Prices on Vehicle Miles Traveled. A preliminary Economic Inquiry, Presentation in Farmers Insurance Group, September 2007

McGuckin N., and S. Liss. (2005). Aging Cars, Aging Drivers: Important Findings from the National Household Travel Survey. *ITE Journal*, 75(9), 30-37.

National Surface Transportation Policy and Revenue Study Commission, Implications of Rising Household Income on Passenger Travel Demand. Commission Briefing Paper 4A-06. Prepared by: Section 1909 Commission Staff Date: January 16, 2007. This paper is part of a series of briefing papers to be prepared for the National Surface Transportation Policy and Revenue Study Commission authorized in Section 1909 of SAFETEA-LU.

National Surface Transportation and Revenue Study Commission. Transportation for Tomorrow. Report of the National Surface Transportation and Revenue Study Commission. December 2007.

Newman, P., and J. Kenworthy. (1999). Costs of Automobile Dependence: Global Survey of Cities. *Transportation Research Record*, 1670, 17–26.

Noland, R., and W. Cowart. (2000). Analysis of metropolitan highway capacity and the growth in vehicle miles of travel. *Transportation*, 27 (4), 363-390.

Noland, R. (2001). Relationships between highway capacity and induced vehicle travel. *Transportation Research*, A (35), 47-72.

Polzin, S., X. Chu, and L. Toole-Holt. (2004). Forecasts of future vehicle miles of Travel in the United States. *Transportation Research Record*, 1895, 147-155.

Polzin, S. (2006).The Case for Moderate Growth in Vehicle Miles of Travel: A Critical Juncture in U.S. Travel Behavior Trends. Prepared for U.S. Department of Transportation.

Puentes, R. and A. Tomer. (2008) *The Road…Less Traveled: An analysis of Vehicle Miles Traveled Trends in the U.S.* Brookings, Washington. D.C.

Singh, M., A. Vyas, and E. Steiner (2003). VISION Model: Description of the Model Used to Estimate the Impact of Highway Vehicle Technologies and Fuels on Energy Use and Carbon Emission to 2050. Center for Transportation Research, Energy Systems Division, Argonne National Laboratory. Argonne, Illinois.

Souleyrette, R., Z. Hans, W. Garrison, and L. Wazny. (1995). Analysis of Trends Underlying Urban/ Regional Impacts of Traffic Growth. *Journal of Urban Planning and Development*, 158-171.

Southworth, F. (2001). On the potential impacts of land use change policies on automobile vehicle miles of travel. *Energy Policy*, 29, 1271-1283.

Stone, B., W. Obermann and S. Snyder. (2005). A new method for estimating and projecting vehicle miles of travel. North Central Research Station. Forest Service U.S. Department of Agriculture, St. Paul, MN.

Strathman, J., J. Dueker, T. Sanchez, J. Zhang, and A. Riis. (2000). Analysis of induced travel in the 1995 NPTS. Washington, DC: U.S. Environmental Protection Agency, Office of Transportation and Air Quality.

The Transportation Sector Model of the National Energy Modeling System. (2001).Office of Integrated and Forecasting, Energy Information Administration, U.S. Department of Energy, Washington D.C.

Transportation Research Board. (1995). Expanding metropolitan highways: Implications for air quality and energy use. Special Report 245. Washington, D.C.: National Research Council, National Academy Press.

Ward, J. 2008. VISION 2008 User's Guide. Vehicle Technologies Program. U.S. Department of Energy, Energy Efficiency and Renewable Energy.

Washington, S., Karlaftis, M., and Mannering, F. (2003). *Statistical and Econometrics Methods for Transportation Data Analysis*. Chapman and Hall/ CRC, Boca Raton, FL, 2003.

APPENDIX A

1. SURE models for rural roads

Interstates

```
+---------------------------------------------------+
| Estimates for equation: X21                        |
| Generalized least squares regression               |
| Model was estimated Apr 12, 2010 at 10:43:25AM     |
| LHS=X21      Mean                 =   9.508826     |
|              Standard deviation   =   .3305748     |
| WTS=none     Number of observs.   =        419     |
| Model size   Parameters           =         20     |
|              Degrees of freedom   =        399     |
| Residuals    Sum of squares       =   6.610942     |
|              Standard error of e  =   .1287198     |
| Fit          R-squared            =   .8480192     |
|              Adjusted R-squared   =   .8407820     |
| Model test   F[ 19,   399] (prob) = 117.18 (.0000) |
| Diagnostic   Log likelihood       =   274.7106     |
|              Restricted(b=0)      =  -130.2342     |
|              Chi-sq [ 19]  (prob) = 809.89 (.0000) |
| Info criter. LogAmemiya Prd. Crt. =  -4.053607     |
|              Akaike Info. Criter. =  -4.053679     |
| Not using OLS or no constant. Rsqd & F may be < 0. |
| Log|W|     -23.9020 Log-Likelihood  =    2629.3304 |
| Durbin-Watson 1.804 Autocorrelation =        .0978 |
| RHO used for GLS        .8268             |
+---------------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
 Constant|    3.16043339       .69629296     4.539   .0000
 X36     |     .02248630       .00190656    11.794   .0000   80.5546778
 X37     |     .02487153       .00209440    11.875   .0000   10.0738663
 X38     |     .00389684       .00097601     3.993   .0001   8.90541766
 X42     |     .01727486       .01156898     1.493   .1354   49.2211695
 X47     |   -.05753995       .01737452    -3.312   .0009   2.30278401
 X53P    |     .08906295       .02459175     3.622   .0003   3.12825545
 X130P   |     .48015232       .03092777    15.525   .0000   6.79689483
 ARIZONA |     .16782466       .03120406     5.378   .0000    .02147971
 ARKANSAS|   -.09153514       .03001033    -3.050   .0023    .02147971
 CALIFORN|     .17298215       .03483880     4.965   .0000    .01909308
 Y2000   |   -.00670822       .00405854    -1.653   .0984    .11217184
 CONNECTI|   -.18601755       .02660651    -6.991   .0000    .01909308
 NEBRASKA|   -.26235904       .02430682   -10.794   .0000    .02147971
 NEVADA  |     .14075489       .02871323     4.902   .0000    .02147971
 KANSAS  |   -.09154375       .02295886    -3.987   .0001    .02147971
 PENNSYLV|     .07521508       .02306436     3.261   .0011    .02147971
 MICHIGAN|   -.24356271       .02499407    -9.745   .0000    .02147971
 MINNESOT|   -.14402482       .02762794    -5.213   .0000    .02147971
 NORTHCAR|   -.13126235       .02433772    -5.393   .0000    .02147971
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Principal Arterials

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+--
-------------------------------------------------+
| Estimates for equation: X22                      |
| Generalized least squares regression             |
| Model was estimated Apr 12, 2010 at 10:43:25AM   |
| LHS=X22      Mean                 =   9.502843   |
|              Standard deviation   =   .3703294   |
| WTS=none     Number of observs.   =        419   |
| Model size   Parameters           =         26   |
|              Degrees of freedom   =        393   |
| Residuals    Sum of squares       =   7.948738   |
|              Standard error of e  =   .1422174   |
| Fit          R-squared            =   .8521685   |
|              Adjusted R-squared   =   .8427645   |
| Model test   F[ 25,   393] (prob) =  90.62 (.0000) |
| Diagnostic   Log likelihood       =   236.1024   |
|              Restricted(b=0)      =  -177.8159   |
|              Chi-sq [ 25]  (prob) = 827.84 (.0000) |
| Info criter. LogAmemiya Prd. Crt. =  -3.840593   |
|              Akaike Info. Criter. =  -3.840753   |
| Not using OLS or no constant. Rsqd & F may be < 0. |
| Log|W|     -23.9020 Log-Likelihood  =    2629.3304 |
| Durbin-Watson 1.887 Autocorrelation =        .0563 |
| RHO used for GLS        .8741            |
+----------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	3.33735419	.34877836	9.569	.0000	
X36	.01857923	.00170540	10.894	.0000	80.5546778
X37	.01639733	.00182274	8.996	.0000	10.0738663
LOGX52	-.08246498	.00827326	-9.968	.0000	4.46730598
X130P	.71284984	.03753351	18.992	.0000	6.79689483
ALABAMA	.15391988	.04879483	3.154	.0016	.01909308
ARIZONA	-.13263176	.03088674	-4.294	.0000	.02147971
COLORADO	-.05941424	.02520400	-2.357	.0184	.02147971
IOWA	.09412212	.02386852	3.943	.0001	.02147971
MISSISSI	.23771262	.04120806	5.769	.0000	.02147971
MISSOURI	.19218423	.02794227	6.878	.0000	.02147971
NEWYORK	-.14340128	.02962609	-4.840	.0000	.02147971
KENTUCKY	.09057599	.03239577	2.796	.0052	.02147971
LOUISIAN	-.16681031	.03399746	-4.907	.0000	.02147971
VERMONT	-.14223449	.03796168	-3.747	.0002	.02147971
WISCONSI	.30536642	.03139897	9.725	.0000	.02147971
NEBRASKA	-.16960480	.02437107	-6.959	.0000	.02147971
FLORIDA	.15439477	.03174450	4.864	.0000	.02147971
MARYLAND	.22455249	.03379288	6.645	.0000	.02147971
TEXAS	.11684416	.02831974	4.126	.0000	.02147971
UTAH	-.30305593	.03758324	-8.064	.0000	.02147971
WASHINGT	-.05030710	.03172055	-1.586	.1128	.02147971
NEWJERSE	.36003483	.02877842	12.511	.0000	.02147971
ILLINOIS	-.22991626	.02513361	-9.148	.0000	.02147971
NORTHCAR	.10705162	.03445984	3.107	.0019	.02147971
NORTHDAC	.13131095	.03069698	4.278	.0000	.02147971

Minor Arterials

```
+----------------------------------------------------+
| Estimates for equation: X23                        |
| Generalized least squares regression               |
| Model was estimated Apr 12, 2010 at 10:43:25AM     |
| LHS=X23      Mean                 =   9.339923     |
|              Standard deviation   =   .4036730     |
| WTS=none     Number of observs.   =        419     |
| Model size   Parameters           =         20     |
|              Degrees of freedom   =        399     |
| Residuals    Sum of squares       =   9.299313     |
|              Standard error of e  =   .1526648     |
| Fit          R-squared            =   .8566306     |
|              Adjusted R-squared   =   .8498035     |
| Model test   F[ 19,   399] (prob) = 125.47 (.0000) |
| Diagnostic   Log likelihood       =   203.2262     |
|              Restricted(b=0)      =  -213.9387     |
|              Chi-sq [ 19]  (prob) = 834.33 (.0000) |
| Info criter. LogAmemiya Prd. Crt. =  -3.712392     |
|              Akaike Info. Criter. =  -3.712465     |
| Not using OLS or no constant. Rsqd & F may be < 0. |
| Log|W|     -23.9020 Log-Likelihood  =    2629.3304 |
| Durbin-Watson 1.843 Autocorrelation =        .0783 |
| RHO used for GLS        .8619            |
+----------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	2.25279394	.35661920	6.317	.0000	
X36	.02400730	.00175771	13.658	.0000	80.5546778
X37	.02087858	.00188826	11.057	.0000	10.0738663
X130P	.65654786	.03472021	18.910	.0000	6.79689483
X55P	.11883386	.02711701	4.382	.0000	3.93950429
SOUTHCAR	.11730453	.02713662	4.323	.0000	.02147971
MAINE	.13148512	.02605485	5.046	.0000	.02147971
MISSISSI	.26862125	.03720498	7.220	.0000	.02147971
GEORGIA	.10910721	.02785411	3.917	.0001	.02147971
FLORIDA	-.20152001	.03111218	-6.477	.0000	.02147971
ALABAMA	.16243070	.04198238	3.869	.0001	.01909308
OHIO	-.13873446	.02375399	-5.840	.0000	.01909308
OREGON	-.15646332	.02251102	-6.951	.0000	.02147971
WASHINGT	-.20511883	.02892628	-7.091	.0000	.02147971
KENTUCKY	-.11278403	.02662207	-4.236	.0000	.02147971
WISCONSI	.25438600	.03002915	8.471	.0000	.02147971
WYOMING	-.14272841	.03224237	-4.427	.0000	.02147971
MARYLAND	.14750299	.02853211	5.170	.0000	.02147971
UTAH	-.28591412	.02940358	-9.724	.0000	.02147971
VERMONT	.13045111	.03200943	4.075	.0000	.02147971

Collectors

```
+----------------------------------------------------+
| Estimates for equation: X24                        |
| Generalized least squares regression               |
| Model was estimated Apr 12, 2010 at 10:43:25AM     |
| LHS=X24      Mean                  =   9.423509    |
|              Standard deviation    =   .4061235    |
| WTS=none     Number of observs.    =        419    |
| Model size   Parameters            =         27    |
|              Degrees of freedom    =        392    |
| Residuals    Sum of squares        =   6.378791    |
|              Standard error of e   =   .1275634    |
| Fit          R-squared             =   .9011051    |
|              Adjusted R-squared    =   .8945457    |
| Model test   F[ 26,   392] (prob) = 137.38 (.0000) |
| Diagnostic   Log likelihood        =   282.1997    |
|              Restricted(b=0)       =  -216.4746    |
|              Chi-sq [ 26]  (prob) = 997.35 (.0000) |
| Info criter. LogAmemiya Prd. Crt. =  -4.055835     |
|              Akaike Info. Criter. =  -4.056014     |
| Not using OLS or no constant. Rsqd & F may be < 0. |
| Log|W|     -23.9020 Log-Likelihood  =    2629.3304 |
| Durbin-Watson 1.757 Autocorrelation =        .1215 |
| RHO used for GLS        .8135             |
+----------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	14.6549832	.94220925	15.554	.0000	
X42	-.24208989	.01694851	-14.284	.0000	49.2211695
X44	.85179576	.11781797	7.230	.0000	4.49902578
X46	-.00311546	.00057353	-5.432	.0000	17.5880668
X140	.00484243	.00121726	3.978	.0001	1.64379475
X55P	.33760823	.09992046	3.379	.0007	3.93950429
X56P	.34372152	.09617855	3.574	.0004	4.45168378
ARKANSAS	.10210210	.04182988	2.441	.0147	.02147971
MISSOURI	.17306191	.04230760	4.091	.0000	.02147971
TEXAS	.43164758	.04199126	10.279	.0000	.02147971
CONNECTI	.28557106	.04269336	6.689	.0000	.01909308
TENNESSE	-.11350389	.04353138	-2.607	.0091	.02147971
OREGON	-.09151073	.03662272	-2.499	.0125	.02147971
INDIANA	.41059266	.03834362	10.708	.0000	.02147971
IOWA	.11547869	.03942298	2.929	.0034	.02147971
WESTVIRG	.12641085	.04340932	2.912	.0036	.02147971
NEWJERSE	.29214301	.05085760	5.744	.0000	.02147971
NEWMEXIC	-.49281735	.05186246	-9.502	.0000	.02147971
SOUTHDAC	-.23747111	.04167472	-5.698	.0000	.02147971
Y2002	.01141029	.00557302	2.047	.0406	.10978520
Y2000	-.01500127	.00794204	-1.889	.0589	.11217184
MONTANA	-.05927442	.04112847	-1.441	.1495	.02147971
NEWHAMPS	.08797994	.04340797	2.027	.0427	.02147971
NEWYORK	-.14501838	.04322218	-3.355	.0008	.02147971
OHIO	.23188630	.03975372	5.833	.0000	.01909308
WISCONSI	.35278476	.04167925	8.464	.0000	.02147971
VERMONT	.11031801	.04052175	2.722	.0065	.02147971

2. SURE models for urban roads

Interstates

```
+----------------------------------------------------+
| Estimates for equation: X26                        |
| Generalized least squares regression               |
| Model was estimated Apr 12, 2010 at 10:51:51AM     |
| LHS=X26      Mean                 =   9.692360     |
|              Standard deviation   =   .5106376     |
| WTS=none     Number of observs.   =        387     |
| Model size   Parameters           =         26     |
|              Degrees of freedom   =        361     |
| Residuals    Sum of squares       =   2.971150     |
|              Standard error of e  =   .9072117E-01 |
| Fit          R-squared            =   .9683543     |
|              Adjusted R-squared   =   .9661627     |
| Model test   F[ 25,   361] (prob) = 441.86 (.0000) |
| Diagnostic   Log likelihood       =   393.1143     |
|              Restricted(b=0)      =  -288.5278     |
|              Chi-sq [ 25]  (prob) =1363.28 (.0000) |
| Info criter. LogAmemiya Prd. Crt. =  -4.734906     |
|              Akaike Info. Criter. =  -4.735109     |
| Not using OLS or no constant. Rsqd & F may be < 0. |
| Log|W|     -28.2945 Log-Likelihood  =    2729.3454 |
| Durbin-Watson 1.755 Autocorrelation =        .1226 |
| RHO used for GLS        .8182               |
+----------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	12.7117527	.70081020	18.139	.0000	
X34	.00573825	.00073615	7.795	.0000	68.7203618
X37	.00541334	.00100276	5.398	.0000	11.2664083
X39	.07367380	.00651127	11.315	.0000	2.58444444
X42	-.10843021	.01413828	-7.669	.0000	49.1419121
X47	-.04299699	.02152088	-1.998	.0457	2.30373204
X60P	.63499609	.01927956	32.936	.0000	2.63884237
X61P	.04033860	.02372831	1.700	.0891	3.06660841
X132	-.02689071	.02037943	-1.320	.1870	.24054677
MISSOURI	.13758684	.03164871	4.347	.0000	.02325581
ARIZONA	-.10858564	.03154486	-3.442	.0006	.02325581
CALIFORN	-.28517994	.05478612	-5.205	.0000	.02067183
UTAH	.34032113	.03371365	10.094	.0000	.02325581
MINNESOT	.18021905	.02799735	6.437	.0000	.02325581
NEWJERSE	-.39999808	.03639613	-10.990	.0000	.02325581
NEBRASKA	-.12599777	.02950103	-4.271	.0000	.02325581
NEWYORK	-.44607444	.03563315	-12.519	.0000	.02325581
VERMONT	-.30406480	.03714207	-8.187	.0000	.02325581
NEWHAMPS	-.06209362	.03618330	-1.716	.0861	.02325581
KENTUCKY	.06408986	.02686043	2.386	.0170	.02325581
GEORGIA	.18786135	.02785739	6.744	.0000	.02325581
OREGON	-.14284495	.02937417	-4.863	.0000	.02325581
PENNSYLV	-.25865078	.03331587	-7.764	.0000	.02325581
VIRGINIA	-.09801832	.02921578	-3.355	.0008	.02325581
WISCONSI	-.20756856	.03126001	-6.640	.0000	.02325581
COLORADO	.08061768	.03360150	2.399	.0164	.02325581

Freeways

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+----------------------------------------------------+
| Estimates for equation: X27                        |
| Generalized least squares regression               |
| Model was estimated Apr 12, 2010 at 10:51:51AM     |
| LHS=X27      Mean                 =   9.097323     |
|              Standard deviation   =   .8295270     |
| WTS=none     Number of observs.   =        387     |
| Model size   Parameters           =         22     |
|              Degrees of freedom   =        365     |
| Residuals    Sum of squares       =   33.58702     |
|              Standard error of e  =   .3033467     |
| Fit          R-squared            =   .8659270     |
|              Adjusted R-squared   =   .8582133     |
| Model test   F[ 21,   365] (prob) = 112.26 (.0000) |
| Diagnostic   Log likelihood       =  -76.16005     |
|              Restricted(b=0)      =  -476.2984     |
|              Chi-sq [ 21]  (prob) = 800.28 (.0000) |
| Info criter. LogAmemiya Prd. Crt. =  -2.330467     |
|              Akaike Info. Criter. =  -2.330590     |
| Not using OLS or no constant. Rsqd & F may be < 0. |
| Log|W|     -28.2945 Log-Likelihood  =    2729.3454 |
| Durbin-Watson 1.875 Autocorrelation =        .0623 |
| RHO used for GLS        .8365             |
+----------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	7.26290415	.81701230	8.890	.0000	
X34	.01227108	.00251970	4.870	.0000	68.7203618
X36	-.06687887	.00756783	-8.837	.0000	79.2611370
X37	-.07272779	.00819160	-8.878	.0000	11.2664083
X38	-.07603121	.00531848	-14.296	.0000	9.37056848
X46	-.00352435	.00173426	-2.032	.0421	16.3253230
X47	.43057411	.12940529	3.327	.0009	2.30373204
X61P	.23083687	.07542391	3.061	.0022	3.06660841
X130P	.87097620	.11574575	7.525	.0000	6.86505221
X132	.33827161	.07106629	4.760	.0000	.24054677
KENTUCKY	-.17517298	.09767709	-1.793	.0729	.02325581
ARKANSAS	.56046548	.10467504	5.354	.0000	.02325581
ILLINOIS	-.53511683	.08585562	-6.233	.0000	.02325581
KANSAS	.58874660	.09483685	6.208	.0000	.02325581
TEXAS	1.33492750	.11634990	11.473	.0000	.02325581
WESTVIRG	-.62689562	.09539765	-6.571	.0000	.02325581
ARIZONA	1.08080566	.10727993	10.075	.0000	.02325581
OKLAHOMA	.64428028	.12188332	5.286	.0000	.02325581
NORTHCAR	.51916754	.09139409	5.681	.0000	.02325581
MARYLAND	.23639740	.09974922	2.370	.0178	.02325581
PENNSYLV	-.25037342	.09592683	-2.610	.0091	.02325581
RHODEISL	.93619971	.11602232	8.069	.0000	.02325581

Principal Arterials

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+----------------------------------------------------+
| Estimates for equation: X28                        |
| Generalized least squares regression               |
| Model was estimated Apr 12, 2010 at 10:51:51AM     |
| LHS=X28      Mean                 =   9.740212     |
|              Standard deviation   =   .4623122     |
| WTS=none     Number of observs.   =        387     |
| Model size   Parameters           =         29     |
|              Degrees of freedom   =        358     |
| Residuals    Sum of squares       =   6.303759     |
|              Standard error of e  =   .1326961     |
| Fit          R-squared            =   .9174020     |
|              Adjusted R-squared   =   .9109418     |
| Model test   F[ 28,   358] (prob) = 142.01 (.0000) |
| Diagnostic   Log likelihood       =   247.5642     |
|              Restricted(b=0)      =  -250.0523     |
|              Chi-sq [ 28]  (prob) = 995.23 (.0000) |
| Info criter. LogAmemiya Prd. Crt. =  -3.967126     |
|              Akaike Info. Criter. =  -3.967408     |
| Not using OLS or no constant. Rsqd & F may be < 0. |
| Log|W|     -28.2945 Log-Likelihood  =    2729.3454 |
| Durbin-Watson 1.781 Autocorrelation =        .1096 |
| RHO used for GLS        .8240             |
+----------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	14.1892693	.88254484	16.078	.0000	
X34	.00955703	.00092039	10.384	.0000	68.7203618
X38	.01413062	.00135339	10.441	.0000	9.37056848
X39	-.04751156	.01019382	-4.661	.0000	2.58444444
X42	-.15118673	.01590519	-9.505	.0000	49.1419121
X46	-.00203732	.00051740	-3.938	.0001	16.3253230
X47	.13336340	.03643312	3.660	.0003	2.30373204
X62P	.55273083	.07220216	7.655	.0000	3.60148923
X134	.16840708	.05778773	2.914	.0036	.45076744
WASHINGT	.11212838	.02906280	3.858	.0001	.02325581
WYOMING	.21071749	.03599415	5.854	.0000	.02325581
INDIANA	.12907947	.02510979	5.141	.0000	.02325581
LOUISIAN	-.06205654	.02689115	-2.308	.0210	.02325581
DELAWARE	-.35893550	.03101114	-11.574	.0000	.02325581
MICHIGAN	.24572353	.02491162	9.864	.0000	.02325581
ILLINOIS	.10310450	.02462923	4.186	.0000	.02325581
RHODEISL	-.23113945	.02878385	-8.030	.0000	.02325581
NEWHAMPS	-.23290917	.02953845	-7.885	.0000	.02325581
NEWMEXIC	-.18835315	.05017967	-3.754	.0002	.02325581
NEVADA	-.31446415	.03801468	-8.272	.0000	.02325581
NORTHCAR	.12242025	.02450589	4.996	.0000	.02325581
OKLAHOMA	.18900402	.03024937	6.248	.0000	.02325581
WESTVIRG	-.28552806	.03418251	-8.353	.0000	.02325581
WISCONSI	.05729592	.03385549	1.692	.0906	.02325581
TEXAS	-.11113454	.03632252	-3.060	.0022	.02325581
VERMONT	-.33948943	.03180318	-10.675	.0000	.02325581
CONNECTI	-.49922749	.03092446	-16.143	.0000	.02067183
CALIFORN	.14703404	.04837776	3.039	.0024	.02067183
MAINE	-.12999862	.02887601	-4.502	.0000	.02325581

Minor Arterials

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+----------------------------------------------------+
| Estimates for equation: X29                        |
| Generalized least squares regression               |
| Model was estimated Apr 12, 2010 at 10:51:51AM     |
| LHS=X29      Mean                 =   9.650600     |
|              Standard deviation   =   .4766769     |
| WTS=none     Number of observs.   =        387     |
| Model size   Parameters           =         23     |
|              Degrees of freedom   =        364     |
| Residuals    Sum of squares       =   8.361272     |
|              Standard error of e  =   .1515603     |
| Fit          R-squared            =   .8986447     |
|              Adjusted R-squared   =   .8925188     |
| Model test   F[ 22,   364] (prob) = 146.70 (.0000) |
| Diagnostic   Log likelihood       =   192.9073     |
|              Restricted(b=0)      =  -261.8939     |
|              Chi-sq [ 22]  (prob) = 909.60 (.0000) |
| Info criter. LogAmemiya Prd. Crt. =  -3.715811     |
|              Akaike Info. Criter. =  -3.715951     |
| Not using OLS or no constant. Rsqd & F may be < 0. |
| Log|W|     -28.2945 Log-Likelihood  =    2729.3454 |
| Durbin-Watson 1.897 Autocorrelation =        .0516 |
| RHO used for GLS        .8764             |
+----------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	9.78654173	.22654584	43.199	.0000	
X34	.00912764	.00102272	8.925	.0000	68.7203618
X36	-.01446769	.00150191	-9.633	.0000	79.2611370
X38	-.00711763	.00115619	-6.156	.0000	9.37056848
X39	.02539750	.00833611	3.047	.0023	2.58444444
LOGX52	-.01454455	.00951534	-1.529	.1264	4.69469595
X63P	.10865393	.04398211	2.470	.0135	3.84887137
X134	.07794599	.05297269	1.471	.1412	.45076744
X152	.00117399	.00055774	2.105	.0353	6.07152455
COLORADO	-.11176813	.02768258	-4.037	.0001	.02325581
MARYLAND	-.17637120	.03189423	-5.530	.0000	.02325581
MASSACHU	.09407513	.03384925	2.779	.0054	.02325581
MICHIGAN	.11569280	.03428103	3.375	.0007	.02325581
MINNESOT	.09298464	.03197994	2.908	.0036	.02325581
MISSISSI	-.37380160	.03335840	-11.206	.0000	.02325581
MISSOURI	-.10981496	.02480091	-4.428	.0000	.02325581
OKLAHOMA	.25221004	.03622560	6.962	.0000	.02325581
OREGON	-.14242400	.02731426	-5.214	.0000	.02325581
DELAWARE	-.29318824	.02591137	-11.315	.0000	.02325581
FLORIDA	.21096304	.03420077	6.168	.0000	.02325581
VERMONT	-.32864039	.02698779	-12.177	.0000	.02325581
NEVADA	-.17728412	.03274779	-5.414	.0000	.02325581
Y2000	.01237811	.00443088	2.794	.0052	.11111111

Collectors

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+----------------------------------------------------+
| Estimates for equation: X30                        |
| Generalized least squares regression               |
| Model was estimated Apr 12, 2010 at 10:51:51AM     |
| LHS=X30      Mean                 =   9.305036     |
|              Standard deviation   =   .4384133     |
| WTS=none     Number of observs.   =        387     |
| Model size   Parameters           =         19     |
|              Degrees of freedom   =        368     |
| Residuals    Sum of squares       =   10.33072     |
|              Standard error of e  =   .1675488     |
| Fit          R-squared            =   .8535670     |
|              Adjusted R-squared   =   .8464045     |
| Model test   F[ 18,   368] (prob) = 119.17 (.0000) |
| Diagnostic   Log likelihood       =   151.9798     |
|              Restricted(b=0)      =  -229.5110     |
|              Chi-sq [ 18]  (prob) = 762.98 (.0000) |
| Info criter. LogAmemiya Prd. Crt. =  -3.525032     |
|              Akaike Info. Criter. =  -3.525111     |
| Not using OLS or no constant. Rsqd & F may be < 0. |
| Log|W|     -28.2945 Log-Likelihood  =    2729.3454 |
| Durbin-Watson 1.916 Autocorrelation =        .0418 |
| RHO used for GLS        .8708             |
+----------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	11.3890811	.94643004	12.034	.0000	
X34	.01141668	.00124962	9.136	.0000	68.7203618
X36	-.01012836	.00246114	-4.115	.0000	79.2611370
X37	.00337254	.00259236	1.301	.1933	11.2664083
X39	.01409453	.00978964	1.440	.1499	2.58444444
X42	-.06124139	.01792046	-3.417	.0006	49.1419121
X46	-.00161785	.00061815	-2.617	.0089	16.3253230
X47	.19926856	.04476638	4.451	.0000	2.30373204
LOGX52	-.03347170	.01343552	-2.491	.0127	4.69469595
X64P	.13831712	.07956668	1.738	.0821	3.79890241
MAINE	.47285725	.03832339	12.339	.0000	.02325581
WISCONSI	-.09981983	.03915612	-2.549	.0108	.02325581
SOUTHCAR	.33739610	.03745874	9.007	.0000	.02325581
ILLINOIS	.17235644	.02981967	5.780	.0000	.02325581
FLORIDA	.37091585	.04271993	8.683	.0000	.02325581
WYOMING	.67019361	.05297938	12.650	.0000	.02325581
NEWHAMPS	.20447381	.03574394	5.721	.0000	.02325581
PENNSYLV	.14625674	.04000580	3.656	.0003	.02325581
RHODEISL	.17387775	.04780352	3.637	.0003	.02325581

3. Random coefficients- Panel data model for total VMT

```
+----------------------------------------------------+
| OLS Starting values for random parameters model    |
| Ordinary    least squares regression               |
| Model was estimated Apr 05, 2010 at 00:05:34PM     |
| LHS=X133     Mean                 =   10.47220     |
|              Standard deviation   =   .4088941     |
| WTS=none     Number of observs.   =        428     |
| Model size   Parameters           =         14     |
|              Degrees of freedom   =        414     |
| Residuals    Sum of squares       =   .6255714     |
|              Standard error of e  =   .3887213E-01 |
| Fit          R-squared            =   .9912375     |
|              Adjusted R-squared   =   .9909624     |
| Model test   F[ 13,   414] (prob) =3602.53 (.0000) |
| Diagnostic   Log likelihood       =   789.7319     |
|              Restricted(b=0)      =  -224.0451     |
|              Chi-sq [ 13]  (prob) =2027.55 (.0000) |
| Info criter. LogAmemiya Prd. Crt. =  -6.462769     |
|              Akaike Info. Criter. =  -6.462792     |
+----------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
X47	.00893506	.02112666	.423	.6723	2.30281051
X49	-.25997629	.04538807	-5.728	.0000	1.30914322
X130P	-.00868176	.01427540	-.608	.5431	6.80226386
X132	-.01211963	.01656231	-.732	.4643	.24010023
X59P	.02862433	.02074277	1.380	.1676	4.40157438
X66P	-.74481434	.24830924	-3.000	.0027	3.75365258
Constant	1.22463463	.87329979	1.402	.1608	
X32	1.63411279	.23818383	6.861	.0000	6.57832710
X34	.00014865	.00032973	.451	.6521	67.1609655
X36	-.00115828	.00030956	-3.742	.0002	80.4054206
X38	.00132859	.00067757	1.961	.0499	8.83950935
X39	-.01560423	.00341969	-4.563	.0000	2.42355140
X44	.36773919	.09000731	4.086	.0000	4.50011141
LOGX52	.00082358	.00484269	.170	.8650	4.50058448

```
+----------------------------------------------+
| Random Coefficients  LinearRg Model          |
| Maximum Likelihood Estimates                 |
| Model estimated: Apr 05, 2010 at 00:05:44PM.|
| Dependent variable                 X133      |
| Weighting variable                 None      |
| Number of observations              528      |
| Iterations completed                101      |
| Log likelihood function        1153.788      |
| Number of parameters                 23      |
| Info. Criterion: AIC =         -4.28329      |
|   Finite Sample: AIC =         -4.27914      |
| Info. Criterion: BIC =         -4.09733      |
| Info. Criterion:HQIC =         -4.21049      |
| Restricted log likelihood      .0000000      |
| Chi squared                    2307.577      |
| Degrees of freedom                    8      |
| Prob[ChiSqd > value] =         .0000000      |
| Sample is 11 pds and      48 individuals.    |
| LINEAR regression model                      |
| Simulation based on 100 random draws         |
```

```
+---------------------------------------------+
+---------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+---------+--------------+----------------+--------+--------+----------+
---------+Nonrandom parameters
 X47     |    -.01421703       .00560299    -2.537   .0112   2.30281051
 X49     |    -.03746087       .01990059    -1.882   .0598   1.30914322
 X130P   |     .05196377       .00514461    10.101   .0000   6.80226386
 X132    |     .01631537       .00504960     3.231   .0012    .24010023
 X59P    |     .06790093       .00879493     7.720   .0000   4.40157438
 X66P    |     .25587230       .11003604     2.325   .0201   3.75365258
---------+Means for random parameters
 Constant|    4.61587862       .40821601    11.307   .0000
 X32     |     .64655303       .10661579     6.064   .0000   6.57832710
 X34     |     .00027510       .00011995     2.293   .0218   67.1609655
 X36     |    -.00210171       .00011625   -18.079   .0000   80.4054206
 X38     |    -.00477610       .00033347   -14.322   .0000   8.83950935
 X39     |     .00359136       .00179383     2.002   .0453   2.42355140
 X44     |     .06692973       .04192316     1.596   .1104   4.50011141
 LOGX52  |    -.00896984       .00178833    -5.016   .0000   4.50058448
---------+Scale parameters for dists. of random parameters
 Constant|     .01509719       .00071805    21.025   .0000
 X32     |     .00430448       .00015108    28.491   .0000
 X34     |     .00020805     .118798D-04    17.513   .0000
 X36     |     .00010954     .906596D-05    12.082   .0000
 X38     |     .00482560       .00011893    40.574   .0000
 X39     |     .00293616       .00028422    10.331   .0000
 X44     |     .00039844       .00017703     2.251   .0244
 LOGX52  |     .00157095       .00015901     9.880   .0000
---------+Variance parameter given is sigma
 Std.Dev.|     .01209152       .00026683    45.316   .0000


Implied standard deviations of random parameters

Matrix S.D_Beta has  8 rows and  1 columns.
              1
        +--------------
       1|     .01510
       2|     .00430
       3|     .00021
       4|     .00011
       5|     .00483
       6|     .00294
       7|     .00040
       8|     .00157
```

APPENDIX B

1) Daily and Long Trips (NHTS)

Total Daily Trips and Total Miles Traveled in Daily Trips, in Billions

	Total trips*	SE	Total miles**	SE
All person trips	411	1.9	4,012	44.9
Person trips by personal vehicle	356	1.9	3,552	41.3
Vehicle trips	235	1.4	2,298	24.4

Long-Distance Trips and Trip Miles by Mode, in Millions

	Total trips (Millions)	SE	Median miles	SE	Total miles (Millions)	SE
Personal vehicle	2,336.1	36.89	194	3	760,324.7	11,695.33
Air	193.3	6.28	2,068	45	557,609.3	25,375.76
Bus	55.4	3.45	287	20	27,081.3	3,048.33
Train	21.1	2.88	192	26	10,546.0	1,998.44
Other	5.8	1.45	188	48	5,117.9	1,123.89
Total	2,611.7	37.70	210	3	1,360,679.1	28,295.42

2) High Speed Rail

Growth Factors

VMT Growth Factors for Cars

InputVMT growth factors for cars when the selected VMT Growth Method is 2 or 3.

MUST specify the first year and first year VMT factor.

Car VMT Factor for the Decade Year	2000	2001 - 2010	2011 - 2020	2021 - 2030	2031 - 2040	1st Year	1st Yr VMT Factor
1			1.0040	0.9940	0.9830	2008	0.9720
2			1.0030	0.9930	0.9820		
3			1.0020	0.9920	0.9800		
4		1.0040	1.0010	0.9910	0.9790		
5		1.0040	1.0000	0.9900	0.9750	CARS	
6		1.0040	0.9990	0.9890	0.9730		
7		1.0040	0.9980	0.9880	0.9720		
8		1.0097	0.9970	0.9870	0.9720		
9		1.0097	0.9960	0.9860	0.9720		
0		1.0097	0.9950	0.9850	0.9720		

VMT Growth Factors for Light Trucks

InputVMT growth factors for light trucks when the selected VMT Growth Method is 2 or 3.

MUST specify the first year and first year VMT factor.

LDT VMT Factor for the Decade Year	2000	2001 - 2010	2011 - 2020	2021 - 2030	2031 - 2040	1st Year	1st Yr VMT Factor

1		1.0040	0.9940	0.9830	2008	0.9720
2		1.0030	0.9930	0.9820		
3		1.0020	0.9920	0.9800		
4		1.0010	0.9910	0.9790		
5		1.0000	0.9900	0.9750	LIGHT TRUCKS	
6	1.0040	0.9990	0.9890	0.9730		
7	1.0040	0.9980	0.9880	0.9720		
8	1.0040	0.9970	0.9870	0.9720		
9	1.0097	0.9960	0.9860	0.9720		
0	1.0097	0.9950	0.9850	0.9720		

Results

	2000	2010	2020	2030	2040
LIGHT DUTY VEHICLES					
Energy Use (quads)	**14.97**	**13.41**	**11.43**	**9.24**	**6.85**
Oil	**14.84**	**12.68**	**10.44**	**8.28**	**6.10**
Percent Oil Reduction	**4.9%**	**21.8%**	**34.7%**	**48.5%**	**63.4%**
CNG	**0.00**	**0.01**	**0.00**	**0.00**	**0.00**
F-T Diesel	**0.00**	**0.00**	**0.03**	**0.08**	**0.08**
Bio-Diesel	**0.00**	**0.00**	**0.01**	**0.01**	**0.01**
Methanol	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Hydrogen	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Electric	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Ethanol	**0.13**	**0.72**	**0.94**	**0.87**	**0.65**
Total - Other Fuels	**0.13**	**0.73**	**0.98**	**0.96**	**0.75**
Oil (Million B/D)	**7.74**	**6.62**	**5.45**	**4.32**	**3.19**
Full Fuel Cycle Carbon Emissions (Mln MT C eqv)	**401.5**	**354.5**	**296.6**	**237.5**	**176.0**
Full Fuel Cycle GHG Emissions (Mln MT CO2 eqv)	**1472.0**	**1300.0**	**1087.5**	**870.7**	**645.4**
Carbon Emissions Chng (%)	**4.9%**	**21.8%**	**35.2%**	**48.9%**	**63.7%**
Fuel Expenditures (Billion 2005$)	**204.1**	**277.2**	**215.7**	**181.3**	**144.4**
Fuel Expenditures as a % of GDP	**1.9%**	**2.0%**	**1.2%**	**0.8%**	**0.5%**
Car	**8.91**	**8.01**	**7.02**	**5.67**	**4.19**
Oil	**8.83**	**7.56**	**6.47**	**5.16**	**3.80**
Percent Oil Reduction	**2.5%**	**-2.4%**	**7.7%**	**26.2%**	**45.0%**
CNG	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
F-T Diesel	**0.00**	**0.00**	**0.01**	**0.02**	**0.02**
Bio-Diesel	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Methanol	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Hydrogen	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Electric	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Ethanol	**0.08**	**0.44**	**0.53**	**0.49**	**0.37**
Full Fuel Cycle Carbon Emissions (MMTCe)	**238.9**	**211.7**	**182.7**	**146.3**	**108.1**
Full Fuel Cycle GHG Emissions (Mln MT CO2 eqv)	**875.8**	**776.2**	**669.9**	**536.4**	**396.2**

3) Alternative Fuel Vehicles

a) Realistic Scenario

Distribution of vehicles

Technology	20400-Cars	2040-Light Trucks
EV	9.40%	9.40%
E-85 FFV	9.50%	9.50%
Diesel	6.50%	6.50%
CNG	0.02%	0.02%
SI HEV on Gasoline	13.00%	13.00%
SI HEV on E85/H2	0.00%	0.00%
Diesel HEV	3.58%	3.58%
SI PHEV	24.00%	24.00%
Diesel PHEV	8.00%	8.00%
Fuel Cell	10.00%	10.00%
Conventional	16.00%	16.0%
TOTAL	**100.0%**	**100.0%**

VMT Growth Factors

VMT Growth Factors for Cars

InputVMT growth factors for cars when the selected VMT Growth Method is 2 or 3.

MUST specify the first year and first year VMT factor.

Car VMT Factor for the Decade Year	2000	2001 - 2010	2011 - 2020	2021 - 2030	2031 - 2040	1st Year	1st Yr VMT Factor
1			1.0097	1.0150	1.0188	2008	1.0097
2			1.0100	1.0154	1.0190		
3			1.0102	1.0159	1.1092		
4		1.0040	1.0103	1.0163	1.0195		
5		1.0040	1.0105	1.0168	1.0200	**CARS**	
6		1.0040	1.0110	1.0172	1.0200		
7		1.0040	1.0120	1.0177	1.0203		
8		1.0040	1.0127	1.0180	1.0204		
9		1.0097	1.0138	1.0183	1.0208		
0		1.0097	1.0146	1.0186	1.0208		

VMT Growth Factors for Light Trucks

InputVMT growth factors for light trucks when the selected VMT Growth Method is 2 or 3.

MUST specify the first year and first year VMT factor.

LDT VMT Factor for the Decade Year	2000	2001 - 2010	2011 - 2020	2021 - 2030	2031 - 2040	1st Year	1st Yr VMT Factor
1		1.0000	1.0097	1.0150	1.0188	2008	1.0097
2			1.0100	1.0154	1.0190		
3			1.0102	1.0159	1.1092		

4	1.0040	1.0103	1.0163	1.0195	
					LIGHT TRUCKS
5	1.0040	1.0105	1.0168	1.0200	
6	1.0040	1.0110	1.0172	1.0200	
7	1.0040	1.0120	1.0177	1.0203	
8	1.0040	1.0127	1.0180	1.0204	
9	1.0097	1.0138	1.0183	1.0208	
0	1.0097	1.0146	1.0186	1.0208	

Results

	2000	2010	2020	2030	2040
LIGHT DUTY VEHICLES					
Energy Use (quads)	14.97	13.93	13.26	13.64	15.68
Oil	14.84	13.17	12.08	11.98	12.85
Percent Oil Reduction	4.9%	18.7%	24.4%	25.4%	22.9%
CNG	0.00	0.01	0.00	0.00	0.00
F-T Diesel	0.00	0.00	0.04	0.16	0.28
Bio-Diesel	0.00	0.00	0.01	0.02	0.04
Methanol	0.00	0.00	0.00	0.00	0.00
Hydrogen	0.00	0.00	0.02	0.09	0.55
Electric	0.00	0.00	0.02	0.12	0.56
Ethanol	0.13	0.75	1.08	1.27	1.41
Total - Other Fuels	0.13	0.76	1.18	1.66	2.84
Oil (Million B/D)	7.74	6.87	6.31	6.25	6.70
Full Fuel Cycle Carbon Emissions (Mln MT C eqv)	401.5	368.3	344.8	355.0	426.5
Full Fuel Cycle GHG Emissions (Mln MT CO2 eqv)	1472.0	1350.4	1264.4	1301.7	1563.9
Carbon Emissions Chng (%)	4.9%	18.7%	24.7%	23.6%	12.0%
Fuel Expenditures (Billion 2005$)	204.1	288.0	250.6	268.3	335.3
Fuel Expenditures as a % of GDP	1.9%	2.0%	1.4%	1.2%	1.2%
Car	8.91	8.32	8.10	8.15	9.23
Oil	8.83	7.86	7.44	7.18	7.49
Percent Oil Reduction	2.5%	-6.4%	-6.0%	-2.8%	-8.4%
CNG	0.00	0.00	0.00	0.00	0.00
F-T Diesel	0.00	0.00	0.02	0.07	0.15
Bio-Diesel	0.00	0.00	0.00	0.01	0.02
Methanol	0.00	0.00	0.00	0.00	0.00
Hydrogen	0.00	0.00	0.02	0.09	0.39
Electric	0.00	0.00	0.02	0.12	0.42
Ethanol	0.08	0.45	0.61	0.68	0.76
Full Fuel Cycle Carbon Emissions (MMTCe)	238.9	219.9	211.6	214.8	255.3
Full Fuel Cycle GHG Emissions (Mln MT CO2 eqv)	875.8	806.3	775.7	787.6	935.9

b) Aggressive Scenario

Distribution of vehicles

Technology	2040-Cars	2040-Light Trucks
EV	13.00%	13.00%
E-85 FFV	10.50%	10.50%
Diesel	1.00%	1.00%
CNG	0.02%	0.02%
SI HEV on Gasoline	14.00%	14.00%
SI HEV on E85/H2	0.00%	0.00%
Diesel HEV	5.00%	5.00%
SI PHEV	29.00%	29.00%
Diesel PHEV	12.00%	12.00%
Fuel Cell	13.50%	13.50%
Conventional	1.98%	2.0%
TOTAL	**100.0%**	**100.0%**

Growth Factors

VMT Growth Factors for Cars

InputVMT growth factors for cars when the selected VMT Growth Method is 2 or 3.

MUST specify the first year and first year VMT factor.

Car VMT Factor for the Decade Year	2000	2001 - 2010	2011 - 2020	2021 - 2030	2031 - 2040	1st Year	1st Yr VMT Factor
1			1.0100	1.0152	1.0194	2008	1.0097
2			1.0104	1.0159	1.0199		
3			1.0109	1.0163	1.0204		
4		1.0040	1.0120	1.0168	1.0208		
5		1.0040	1.0125	1.0172	1.0211	**CARS**	
6		1.0040	1.0129	1.0177	1.0220		
7		1.0040	1.0133	1.0180	1.0230		
8		1.0040	1.0138	1.0183	1.0235		
9		1.0097	1.0142	1.0189	1.0239		
0		1.0097	1.0147	1.0191	1.0239		

VMT Growth Factors for Light Trucks

InputVMT growth factors for light trucks when the selected VMT Growth Method is 2 or 3.

MUST specify the first year and first year VMT factor.

LDT VMT Factor for the Decade Year	2000	2001 - 2010	2011 - 2020	2021 - 2030	2031 - 2040	1st Year	1st Yr VMT Factor
1			1.0100	1.0152	1.0194	2008	1.0097
2			1.0104	1.0159	1.0199		
3			1.0109	1.0163	1.0204		
4		1.0040	1.0120	1.0168	1.0208		
5		1.0040	1.0125	1.0172	1.0211	**LIGHT TRUCKS**	
6		1.0040	1.0129	1.0177	1.0220		
7		1.0040	1.0133	1.0180	1.0230		

8	1.0040	1.0138	1.0183	1.0235
9	1.0097	1.0142	1.0189	1.0239
0	1.0097	1.0147	1.0191	1.0239

Results

	2000	2010	2020	2030	2040
LIGHT DUTY VEHICLES					
Energy Use (quads)	14.97	13.93	13.39	13.83	14.50
Oil	14.84	13.17	12.20	12.15	11.58
Percent Oil Reduction	4.9%	18.7%	23.7%	24.3%	30.5%
CNG	0.00	0.01	0.00	0.00	0.00
F-T Diesel	0.00	0.00	0.05	0.16	0.25
Bio-Diesel	0.00	0.00	0.01	0.02	0.04
Methanol	0.00	0.00	0.00	0.00	0.00
Hydrogen	0.00	0.00	0.02	0.09	0.66
Electric	0.00	0.00	0.02	0.12	0.65
Ethanol	0.13	0.75	1.09	1.29	1.31
Total - Other Fuels	0.13	0.76	1.19	1.68	2.92
Oil (Million B/D)	7.74	6.87	6.37	6.34	6.04
Full Fuel Cycle Carbon Emissions (Mln MT C eqv)	401.5	368.3	348.2	360.0	399.6
Full Fuel Cycle GHG Emissions (Mln MT CO2 eqv)	1472.0	1350.4	1276.8	1319.9	1465.0
Carbon Emissions Chng (%)	4.9%	18.7%	23.9%	22.6%	17.5%
Fuel Expenditures (Billion 2005$)	204.1	288.0	253.0	272.1	311.5
Fuel Expenditures as a % of GDP	1.9%	2.0%	1.4%	1.2%	1.1%
Car	8.91	8.32	8.18	8.26	8.52
Oil	8.83	7.86	7.51	7.28	6.72
Percent Oil Reduction	2.5%	-6.4%	-7.0%	-4.2%	2.6%
CNG	0.00	0.00	0.00	0.00	0.00
F-T Diesel	0.00	0.00	0.02	0.07	0.13
Bio-Diesel	0.00	0.00	0.00	0.01	0.02
Methanol	0.00	0.00	0.00	0.00	0.00
Hydrogen	0.00	0.00	0.02	0.09	0.46
Electric	0.00	0.00	0.02	0.12	0.48
Ethanol	0.08	0.45	0.61	0.69	0.71
Full Fuel Cycle Carbon Emissions (MMTCe)	238.9	219.9	213.6	217.8	239.2
Full Fuel Cycle GHG Emissions (Mln MT CO2 eqv)	875.8	806.3	783.3	798.6	877.2

4) Fuel Tax Growth Factors

VMT Growth Factors for Cars

InputVMT growth factors for cars when the selected VMT Growth Method is 2 or 3.

MUST specify the first year and first year VMT factor.

Car VMT Factor for the Decade Year	2000	2001 - 2010	2011 - 2020	2021 - 2030	2031 - 2040	1st Year	1st Yr VMT Factor
1			0.9970	0.9970	0.9970	2008	0.9970
2			0.9970	0.9970	0.9970		
3			0.9970	0.9970	0.9970		
4		1.0040	0.9970	0.9970	0.9970		
5		1.0040	0.9970	0.9970	0.9970	CARS	
6		1.0040	0.9970	0.9970	0.9970		
7		1.0040	0.9970	0.9970	0.9970		
8		1.0097	0.9970	0.9970	0.9970		
9		1.0097	0.9970	0.9970	0.9970		
0		1.0097	0.9970	0.9970	0.9970		

VMT Growth Factors for Light Trucks

InputVMT growth factors for light trucks when the selected VMT Growth Method is 2 or 3.

MUST specify the first year and first year VMT factor.

LDT VMT Factor for the Decade Year	2000	2001 - 2010	2011 - 2020	2021 - 2030	2031 - 2040	1st Year	1st Yr VMT Factor
1			0.9970	0.9970	0.9970	2008	0.9970
2			0.9970	0.9970	0.9970		
3			0.9970	0.9970	0.9970		
4			0.9970	0.9970	0.9970		
5			0.9970	0.9970	0.9970	LIGHT TRUCKS	
6		1.0040	0.9970	0.9970	0.9970		
7		1.0040	0.9970	0.9970	0.9970		
8		1.0040	0.9970	0.9970	0.9970		
9		1.0097	0.9970	0.9970	0.9970		
0		1.0097	0.9970	0.9970	0.9970		

Results

	2000	2010	2020	2030	2040
LIGHT DUTY VEHICLES					
Energy Use (quads)	**14.97**	**13.75**	**11.43**	**9.97**	**9.14**
Oil	**14.84**	**13.00**	**10.45**	**8.93**	**8.15**
Percent Oil Reduction	**4.9%**	**19.8%**	**34.6%**	**44.4%**	**51.1%**
CNG	**0.00**	**0.01**	**0.00**	**0.00**	**0.00**
F-T Diesel	**0.00**	**0.00**	**0.03**	**0.08**	**0.11**
Bio-Diesel	**0.00**	**0.00**	**0.01**	**0.01**	**0.02**
Methanol	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Hydrogen	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Electric	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

Ethanol	0.13	0.74	0.94	0.94	0.87
Total - Other Fuels	0.13	0.75	0.99	1.04	0.99
Oil (Million B/D)	7.74	6.79	5.45	4.66	4.25
Full Fuel Cycle Carbon Emissions (Mln MT C eqv)	401.5	363.7	296.7	256.2	235.0
Full Fuel Cycle GHG Emissions (Mln MT CO2 eqv)	1472.0	1333.4	1088.0	939.4	861.6
Carbon Emissions Chng (%)	4.9%	19.7%	35.2%	44.9%	51.5%
Fuel Expenditures (Billion 2005$)	204.1	284.3	215.8	195.6	192.7
Fuel Expenditures as a % of GDP	1.9%	2.0%	1.2%	0.9%	0.7%
Car	8.91	8.21	7.02	6.12	5.60
Oil	8.83	7.76	6.48	5.56	5.07
Percent Oil Reduction	2.5%	-5.0%	7.7%	20.4%	26.6%
CNG	0.00	0.00	0.00	0.00	0.00
F-T Diesel	0.00	0.00	0.01	0.02	0.03
Bio-Diesel	0.00	0.00	0.00	0.00	0.00
Methanol	0.00	0.00	0.00	0.00	0.00
Hydrogen	0.00	0.00	0.00	0.00	0.00
Electric	0.00	0.00	0.00	0.00	0.00
Ethanol	0.08	0.45	0.53	0.52	0.49
Full Fuel Cycle Carbon Emissions (MMTCe)	238.9	217.1	182.8	157.8	144.2
Full Fuel Cycle GHG Emissions (Mln MT CO2 eqv)	875.8	796.1	670.2	578.8	528.9

5) Density Growth Factors

VMT Growth Factors for Cars

InputVMT growth factors for cars when the selected VMT Growth Method is 2 or 3.
MUST specify the first year and first year VMT factor.

Car VMT Factor for the Decade Year	2000	2001 - 2010	2011 - 2020	2021 - 2030	2031 - 2040	1st Year	1st Yr VMT Factor
1			1.0097	1.0006	1.0006	2008	1.0006
2			1.0097	1.0006	1.0006		
3			1.0097	1.0006	1.0006		
4		1.0040	1.0097	1.0006	1.0006		
5		1.0040	1.0006	1.0006	1.0006	CARS	
6		1.0040	1.0006	1.0006	1.0006		
7		1.0040	1.0006	1.0006	1.0006		
8		1.0040	1.0006	1.0006	1.0006		
9		1.0097	1.0006	1.0006	1.0006		
0		1.0097	1.0006	1.0006	1.0006		

VMT Growth Factors for Light Trucks

InputVMT growth factors for light trucks when the selected VMT Growth Method is 2 or 3.

MUST specify the first year and first year VMT factor.

LDT VMT Factor for the Decade Year	2000	2001 - 2010	2011 - 2020	2021 - 2030	2031 - 2040	1st Year	1st Yr VMT Factor
1			1.0097	1.0006	1.0006	2008	1.0006
2			1.0097	1.0006	1.0006		
3			1.0097	1.0006	1.0006		
4			1.0097	1.0006	1.0006		
5			1.0006	1.0006	1.0006	LIGHT TRUCKS	
6		1.0040	1.0006	1.0006	1.0006		
7		1.0040	1.0006	1.0006	1.0006		
8		1.0040	1.0006	1.0006	1.0006		
9		1.0097	1.0006	1.0006	1.0006		
0		1.0097	1.0006	1.0006	1.0006		

Results

	2000	2010	2020	2030	2040
LIGHT DUTY VEHICLES					
Energy Use (quads)	14.97	13.80	12.34	11.15	10.60
Oil	14.84	13.05	11.27	9.99	9.45
Percent Oil Reduction	4.9%	19.5%	29.5%	37.8%	43.3%
CNG	0.00	0.01	0.00	0.00	0.00
F-T Diesel	0.00	0.00	0.04	0.09	0.13
Bio-Diesel	0.00	0.00	0.01	0.01	0.02
Methanol	0.00	0.00	0.00	0.00	0.00
Hydrogen	0.00	0.00	0.00	0.00	0.00
Electric	0.00	0.00	0.00	0.00	0.00
Ethanol	0.13	0.74	1.01	1.05	1.00
Total - Other Fuels	0.13	0.75	1.06	1.16	1.15
Oil (Million B/D)	7.74	6.81	5.88	5.21	4.93
Full Fuel Cycle Carbon Emissions (Mln MT C eqv)	401.5	365.0	320.1	286.5	272.5
Full Fuel Cycle GHG Emissions (Mln MT CO2 eqv)	1472.0	1338.2	1173.7	1050.6	999.0
Carbon Emissions Chng (%)	4.9%	19.5%	30.1%	38.4%	43.8%
Fuel Expenditures (Billion 2005$)	204.1	285.4	232.8	218.8	223.4
Fuel Expenditures as a % of GDP	1.9%	2.0%	1.3%	1.0%	0.8%
Car	8.91	8.24	7.58	6.84	6.49
Oil	8.83	7.79	6.99	6.22	5.87
Percent Oil Reduction	2.5%	-5.4%	0.4%	11.0%	14.9%
CNG	0.00	0.00	0.00	0.00	0.00
F-T Diesel	0.00	0.00	0.01	0.03	0.04
Bio-Diesel	0.00	0.00	0.00	0.00	0.01
Methanol	0.00	0.00	0.00	0.00	0.00
Hydrogen	0.00	0.00	0.00	0.00	0.00
Electric	0.00	0.00	0.00	0.00	0.00
Ethanol	0.08	0.45	0.57	0.59	0.57

Full Fuel Cycle Carbon Emissions (MMTCe)	**238.9**	**217.9**	**197.2**	**176.5**	**167.2**
Full Fuel Cycle GHG Emissions (Mln MT CO2 eqv)	**875.8**	**799.0**	**723.0**	**647.3**	**613.2**