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The gasoline tax, the main source of highway revenue is no longer a viable source of funding to maintain the existing highways. Many states in the United States are already using revenues from other sources such as sales tax and income tax to fund new highways. Oregon along with many other states is looking into other alternatives such as a distance based mileage fee to generate sufficient highway revenues. The technology required to achieve this has already been tested in Portland. One of the greatest concerns of a vehicle mileage fee is its impacts on the lower income groups and rural households. Critics argue that a distance based fee might discourage the use of fuel efficient vehicles.

The objective of this study is to evaluate these socio economic impacts of shifting from a gasoline tax to a vehicle mileage fee on Oregon households using a discrete continuous choice modeling approach (DCC). DCC is a disaggregate modeling approach and has dominated the recent vehicle ownership models due to its ability to model the distributional and behavioral effects of an individual.

The empirical results indicate that the vehicle mileage fee is only slightly more regressive than a gasoline tax and it increases the social welfare of higher income groups and the people living in the urban areas. The impact of VMT fee on the household's preference to own fuel efficient vehicles did not produce consistent results due to insufficient data. Overall, the DCC approach proved to be an effective tool in estimating the impacts and future research could be carried out in this direction.

Estimating the Impacts of a Vehicle Mileage Fee using a Discrete Continuous Choice Modeling Approach

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

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1.0 INTRODUCTION

Prior to the modern era (15th century), roads were financed locally. People living on the properties adjoining to the roads paid for them. Other people using these roads did not pay for it. The movement of the goods and traffic increased on the roads as a result of the industrial revolution thereby burdening the property owners and the local tax payers. Hence, it became necessary to look for alternative methods of financing these roads. The first turn pike was established in Great Britain in 1663. The first toll road in U.S was the Pennsylvania turn pike established in 1792. The turn pike era ended in the 19th century with the advent of rail transportation, and it became necessary to look for other means of financing the roadways [Lay and Vance, 1992].In 1956 the Highway Trust fund was established to ensure sources of financing for the Interstate and other federal highways. Tax revenues for this are derived from motor fuel taxes, truck sales and vehicle use [NorthEast Midwest Institute, 2008].

Oregon was one of the first states in the U.S. to implement a gasoline tax of 1 cent per gallon in 1919. The tax was used as a source of revenues to generate funds for the maintenance and construction of new roads. However, this gas tax is no longer an economically viable means of generating revenue for highway projects [Whitty, 2007], due to the inadequate increase of gasoline tax with rising inflation. This issue has gained national concern over the recent years. World gasoline prices have been rising steadily and have reached a record high this year. There is already an uproar regarding this issue and an increase in gasoline tax further increases the gas price as a whole. With these soaring gas prices, efforts are being made to introduce more fuel efficient vehicles into the markets. Though this is an environmental friendly approach, it leads to deterioration of the highway revenues. The increased traffic on the roads, higher prices of construction materials and the increase in the Hybrid/Alternate fuel vehicles further shows the inadequacy of gasoline tax as a long term source for funding highway projects. In the recent years, many states in the U.S turned to sales tax increases to pay for transportation improvements [Goldman and Wachs, 2003] despite the fact that payment of sales tax is unrelated to transportation/road use creating inequity.

Among the industrial nations, Great Britain has the highest gasoline tax and the United States has the lowest. Great Britain has been able to generate revenue in gasoline tax equal to nearly one fourth of the revenue that is generated from its income tax. The high gasoline taxes in Great Britain permit the country to increase the price of driving which indirectly reduces the congestion and the traffic accidents on the road [Parry and Small, 2002]. According to the American Petroleum Institute (API) energy report 2008, the average gasoline state tax in the United States is 18 cents per gallon and for Oregon is 24 cents per gallon. The current gasoline tax of 24 cents per gallon for Oregon has been the same since 1991. The gasoline tax still remains the same despite the increase in gasoline prices. Oregon's population is expected to reach 4.8 million by 2030 and the population of United States to 363 million [U.S Census 2000] thereby increasing the annual miles driven and the road wear. The vehicle miles traveled (VMT) is expected to increase by 1.35 percent annually through 2030 for Oregon [Oregon Transportation Plan, 2006].

A few of the alternatives to combat the problem of insufficient funds to finance the highways include privatizing the roads, adding tolls, increasing the gasoline tax or charging a fee according to the vehicle miles traveled also known as the distance-based user fee. VMT fee (distance-based user fee) is the most promising among these alternatives. A difference between user fee and gasoline tax is worth mentioning here. The gasoline tax charges the users according to the average cost of using the transportation system and the revenue collected from this is not entirely confined to building and maintaining the roads. Williams [2006] states that over 15 percent of the tax revenue from the Highway trust fund is diverted for the maintenance of the mass transit. A user fee on the other hand, charges the user according to the miles traveled and the revenue collected is used exclusively to maintain the roads.

The gasoline tax was implemented to maintain the existing highways and the users using the road should pay for it. The road usage is dependent on the mileage and the vehicle weight. Gasoline tax is therefore directly related to the mileage and the vehicle weight. Initially, the gas tax in Oregon was an efficient user fee. Before the advent of fuel efficient vehicles, all the vehicles achieved the same approximate gas mileage. If the person drove more, he or she paid for the extra burden imposed on the roadway [Road User Fee Pilot Program, 2007]. In the present day, the gasoline tax is not proportional to the road damage as fuel efficient vehicles achieving more miles per gallon pay lower per mile fee irrespective of damage imposed on the roads. Oregon established a Road User Fee Task Force (RUFTF) to look into this issue. The RUFTF concluded that the VMT fee is the most feasible alternative. Normally a user imposes internal costs and external costs on the roads. Internal costs such as the vehicle price, operating costs and fuel prices are perceivable by the user. External costs such as congestion, environmental impacts are not perceivable by the user and he or she does not pay for it. The VMT fee can be adjusted in the future if required to account for these external costs according to the time of day to mitigate peak period congestion and by regions. Economists believe that a distance based user charge is a more efficient way of generating revenue which will make the drivers realize the costs and avoid making unnecessary trips which in turn can reduce congestion, fuel consumption and improve the environment [Litman,1999]. Such a fee might also encourage people to shift to other modes such as car pooling or public transit. People may reduce the total miles driven by changing their route choices, trip frequency, origins, destinations etc. In the long run, people may choose to change their residential and work place preferences which can affect the land use. A study conducted in Portland [Whitty and Imholt, 2005] strengthens this observation which concluded that people on an average reduced the number of miles driven because of more awareness when they were charged according to the miles driven.

A study was conducted recently in Portland to test the feasibility of the VMT evaluation technology. This technology [Whitty and Imholt, 2005] consists of onboard devices installed in each vehicle and the use of global positioning system [GPS-AVI] technologies to track the vehicle miles and charge the user based on the geographic location. However, the policy makers in Oregon face certain equity issues with regard to the income groups and region. Policy makers believe that the burden of the VMT fee will be shifted to the lower income groups and also to people living in the rural regions thereby causing geographical inequity. Critics also argue that the VMT fee will discourage people from buying hybrid or fuel efficient vehicles.

Previous studies [McMullen and Zhang, 2008] have been conducted to check the efficiency of certain econometric models to assess the impacts of a vehicle mileage fee such as the Static model, Ordinary least squares regression and Simultaneous equation model. Using the 2001 National household travel survey, this paper quantifies the impacts of a VMT fee on the different income groups and regions using a discrete continuous choice model. Section two provides a summary of the theory of road pricing and the different modeling approaches. Section three examines the previous studies on discrete choice models. Sections four and five outline the methodology and data. Sections six and seven include the estimation results and conclusions.

2.0 THEORY

It is the general rule of road pricing that all the transport services should be priced at marginal costs. Marginal costs can be defined as the increase in the total cost that occurs as a result of providing an extra unit. In theory, the marginal cost should be equal to the price of providing that unit, i.e. people make an extra trip only when the value of making that trip to them is equal to the marginal cost. Road pricing should be able to recover the user charges so as to reflect the specific charges made by each user [Gomez, 1999]. Road pricing should cover the real costs and can include any charges imposed on the user for using the road be it the fuel charges, tolling, license charges etc.

The principle of road pricing can be defined as follows

"*Users should be charged for all the additional costs they impose by their use of the road system– road wear and tear, delays to other users, increased accident risk and environmental cost. The term used to refer to these additional costs is marginal external cost (MEC). When these are added to those costs borne directly by the user (e.g. fuel, their own time) the result is called marginal social cost (MSC). Only when they face all these costs will users have the right incentive to choose whether to make the journey at all, or to adapt destination, mode of transport, route and time of travel in such a way that the overall costs of transport are reduced.*" [Nash et al, 2004].

Different pricing policies can be adopted to cover these external costs. Litman (1999) suggests that distance based fees are the best way to account for these external charges including road use, insurance, pollution emissions and other environmental impacts. Our model ignores these externalities. However, the VMT fee can be adjusted to account for these externalities.

Equity concerns are a major issue in implementing transportation policies. Income and location are the social indicators in determining the impacts of any policy. Critics argue that charging the users on a per mile basis might affect the people belonging to the lower income groups than the higher income groups and people living in the rural areas compared to the urban areas. This study focuses on examining the welfare impacts of shifting to a VMT fee from a gasoline tax.

Different modeling approaches can be followed to model the impacts of the VMT fee namely, static model, simultaneous equation model (SEM), ordinary least squares regression (OLS) and the discrete continuous choice (DCC) model. Nakahara (2007) compared these different modeling approaches for estimating the impacts of the VMT fee on Oregon households.

The Static model assumes that there would be no behavioral changes and everybody drives the same miles irrespective of the tax. The household expenditures under a VMT fee are calculated and subtracted from the household expenditure under a gasoline tax. A negative value indicates an increase in household expenditures under a VMT fee and a positive value indicates otherwise.

The Simultaneous equation model (SEM) assumes that the households vehicle choice, fuel efficiency, vehicle use are interdependent and households choose them simultaneously. Vehicle number choice (*V*) is a function of the vehicle use (*M*), vehicle fuel efficiency (P_m), vehicle price (P_v), income (*I*), location (*U*) and other household characteristics (*HH*). It assumes that all vehicle related choices are continuous. It can be represented as

$$V = x(M, P_m, P_v, I, U, HH) \qquad \textbf{(2-1)}$$

Similarly, vehicle fuel efficiency (P_m) is dependent on the miles traveled (*M*), the vehicle number choice *(V)*, vehicle price *(P_v)*, income *(I)*, location *(U)* and other household characteristics *(HH)*. It can be represented as

$$P_m = y(M, V, P_v, I, U, HH) \qquad \textbf{(2-2)}$$

The miles traveled is a function the vehicle number choice *(V)*, vehicle fuel efficiency *(P_m)*, income *(I)*, location *(U)* and other household characteristics *(HH)*. It can be represented as

$$M = z(V, P_m, I, U, HH) \qquad \textbf{(2-3)}$$

The price variable can interact with the income and location to consider any distributional effects due to the price changes. Similarly, the interaction between fuel efficiency and income can capture the distributional effects between the various income groups. The regression model assumes that the vehicle use depends on the fuel cost per mile, vehicle substitution and other household characteristics.

$$M = f(P_m, I, U, HH) \tag{2-4}$$

The discrete continuous choice (DCC) modeling approach assumes that given the choices of vehicle quantity and type, households choose how many miles to drive on each vehicle. In the vehicle quantity and type the dependent variable can only take a discrete value that is distinct from the vehicle use which is continuous. Both these choices are consistent with the utility maximization behavior.

Random utility theory forms the basis for a discrete choice analysis. It can be represented as a mathematical function which predicts a decision maker's choice based on the utility. The analyst is assumed to have incomplete data and hence the uncertainty component should be taken in to account [Moshe and Lerman, 1985].

$$U_{in} = V_{in} + e_{in}\ ; \quad U_{jn} = V_{jn} + e_{jn} \tag{2-5}$$

Where, U_{in} and U_{jn} represent the utility of the individual n choosing alternative 'i' and 'j' respectively. V_{in} and V_{jn} represent the systematic utility as the same functional form applies to all decision makers. e_{in} and e_{jn} are called the random components as they capture the uncertainty due to the unobserved alternative attributes, unobserved individual attributes, etc that varies across the decision makers. Therefore, the probability that alternative 'i' is chosen by the decision maker 'n' can be represented as

$$P_n(i) = Prob\left[U_{in} > U_{jn}\ for\ all\ j \neq i\right] \tag{2-6}$$

The simplest choice model is known as the Binary Probit which involves only two alternatives. When there are more than two choice alternatives, the model is known as multinomial logit or just logit. It can be defined as

$$P_{in} = \frac{e^{V_{in}}}{\sum_{j=1}^{j_n} e^{V_{jn}}} \qquad \text{for all } i \text{ and } j \tag{2-7}$$

Where P_i the probability of choosing alternative 'i' from a choice set 'J_n '. A Multinomial logit model is based on the property of Independence from Irrelevant Alternatives (IIA) which implies that the ratio of the probabilities between alternatives 'i' and 'j' is independent of the utilities of any other alternatives. Nested logit models are those in which the user makes choices simultaneously and does not necessarily have to obey the IIA property [Small and Winston, 1999].

3.0 PREVIOUS STUDIES

Discrete choice models or qualitative choice models predict the decisions made by an individual (vehicle ownership choice, mode choice, vehicle use, etc.) as a function of a number of factors which seem to influence the decision making process. The individual is presumed to have made the choice from a discrete set. Discrete choice models are widely used to predict the mode choice of individuals in transportation modeling. The most prominent discrete choice models used currently include logit, generalized extreme value, probit, and mixed logit. These models can effectively analyze the variables which are not continuous but still vary over time. Regression models on the other hand can effectively analyze the continuous variables. When an individual is provided with two qualitative choices such as the number of cars to own or the number of miles to drive, the first choice is between a discrete set of alternatives say 0, 1 or 2. The second choice is among a continuous set of alternatives such as any number of miles. A discrete choice model can be used to estimate the first choice but cannot estimate the second one. Thus, in most of the studies which have used this approach the vehicle number choice is estimated using a discrete choice model and then vehicle use (miles traveled) is estimated using linear regression. In this case we need both a discrete and continuous model [Train, 1986]. Hence, a combination of these two models known as the discrete-continuous choice (DCC) model can be used here.

DCC models have dominated the recent vehicle ownership studies. The DCC model was introduced by Dubin and McFadden (1984) when they suggested that, in order to estimate the demand for electricity, a derived demand, one has to simultaneously estimate the demand for the durables that ultimately drive the demand for energy. West (2001) used this approach to examine the distributional effects of vehicle pollution control policies by estimating the joint demand for vehicles and miles. Train (1986) estimated the demand for cars and light trucks while taking into account the interdependence between the number of vehicles a household chooses to own and the type chosen. Mohammadian and Miller (2003) developed a household automobile type choice model at a disaggregate level to estimate the consumer demand for personal-use vehicles given the available choices. Mannering and Winston (1985) used this approach to analyze the impact of vehicle ownership on the utilization. Other people who have used this approach include Lave and Train (1979) and Berkowitz (1990). Ramjerdi and Rand (1992) and Dejong (1990) used a DCC vehicle ownership and use model to predict that changes in fuel cost per mile not only affects the annual miles driven by a household but also the number of vehicles owned. Goldberg (1998) developed a discrete choice model of automobile demand and a continuous model of vehicle utilization to estimate the effects of the corporate average fuel efficiency standards.

Gasoline taxes are known to be regressive. A regressive tax takes a higher percentage of income from lower income people than from higher income people and a progressive tax is otherwise. An increase in the price of any commodity puts a greater burden on the poorer households when consumed at the same levels. In such situations, people tend to change their consumption levels to reduce the costs. Santos and Catchesides (2005) assessed the regressive nature of a gasoline tax in U.K and concluded that gasoline taxes are strongly regressive only when the car owning households are considered. When all households are considered middle income households share most of the burden. The demand for mileage is more price elastic and income elastic for the poorer households than the higher income households which implies that poorer households are more sensitive to the fuel taxes. However, in the long run the authors state that the low income households reduce the impacts of the fuel taxes by changing the vehicle holdings and efficiency of the vehicles.

Poterba (1990) demonstrates that gasoline tax is not regressive when household expenditures are considered instead of the income. West (2001) also addresses the regressive nature of the gasoline tax in her study by including the households owning zero vehicles. She concludes that the gasoline tax is not as regressive as it is thought to be because households with a lower annual income spend a smaller percentage of income on gasoline tax and hence gasoline tax is progressive over low income households and regressive over the high income earning families. The same approach is followed here and hence households with zero vehicles are also included in our study even though these households may not be directly impacted by this policy.

4.0 METHODOLOGY

The model adopted here is similar to the one proposed by Kenneth Train (1986). It is based on the assumption that households will simultaneously choose the number of vehicles to own, the type of vehicle and the annual miles driven on each vehicle.

The discrete-continuous model consists of a discrete model for the vehicle number choice and the vehicle type and a continuous model for the vehicle miles driven. A household first chooses the number of vehicles to own as shown in Figure 1. Based on the number of vehicles, it then chooses the types of vehicles to own. A household owning a single vehicle can own either a car or truck. Households owning two vehicles can choose to own either cars or trucks, or a car and a truck. Similarly, households with three vehicles can choose between all cars, all trucks, two cars and a truck, or two trucks and a car. As the vehicles a household chooses to own increases, the options available for the types or combinations of vehicles to own also increases. Households owning more than three vehicles are not considered for this analysis as there are not enough observations to obtain credible results.

The vehicle usage, i.e., vehicle miles driven, by each household is dependent on the type of vehicles it owns. This model can be run at both the household level and then vehicle level; i.e., the total annual miles for each household can be taken as the dependent variable, or the vehicle miles driven for each vehicle can be considered. The vehicle level model requires more data and hence the vehicle-miles-driven model at the household level is considered for our analysis. The diagrammatic representation is shown in Figure 1.

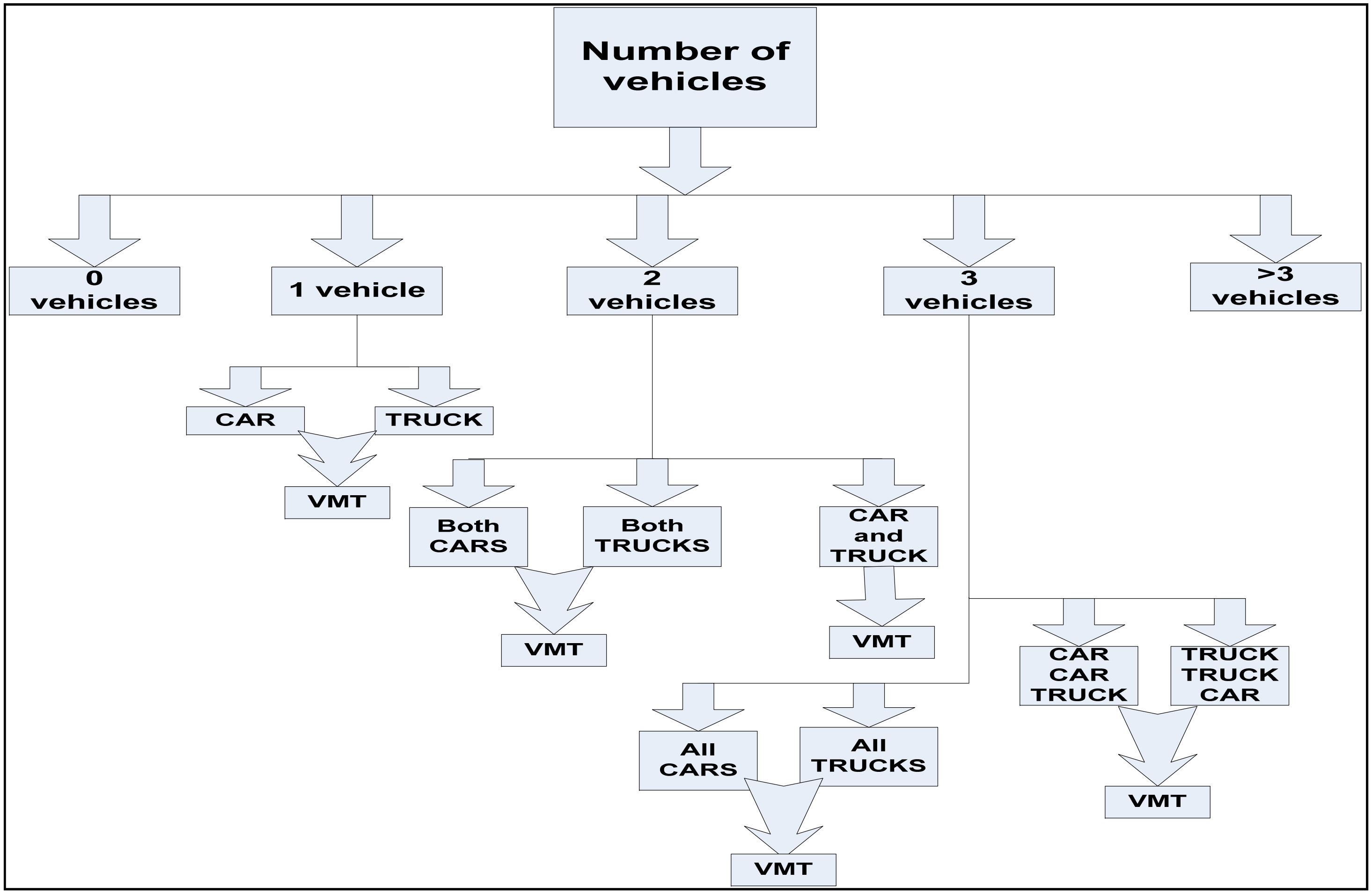

Figure 1: Diagrammatic representation of the discrete-continuous choice model

4.1 HOUSEHOLD CHARACTERISTICS

Income is an important determinant of vehicle ownership and use in any model. It is one of the important variables in explaining the variations in car ownership and in policy analysis. It is generally assumed that if a household has higher income, the probability it chooses to own a specified number of vehicles is greater compared to a lower income household. This may not always be true. Income is related to household size in some cases. Even though a household's income might be more, it might spend a larger proportion of money on other essential goods due to the large household size and have less money for other expenditure such as owning multiple vehicles [Han, 2002]. The location of a household is one other important variable in evaluating a policy especially a distance based user fee. Bhat (2004) and Zhao (2000) in their study show that households living in densely populated areas do not prefer to own pickup trucks.

Household size, children and the number of working people also play a significant role in determining the vehicle holdings and vehicle use of a household. If there are more workers in a household, it requires more mobility. Hence, a household might prefer to own a car. Similarly, the presence of children plays an important role in choosing the type of vehicle to own. Households usually prefer to own a large vehicle such as a SUV to accommodate children. Bhat and Sen (2004) in their study predict that households with children less than 4 years of age prefer to own SUV's and minivans.

People with a higher level of education are more likely to have a job in the city thereby having better access to the public transit. We can expect that education is negatively proportional to the vehicle ownership. At the same time, educated people are more aware of the environment and capital costs and try to own fuel efficient vehicles. Manski and Sherman (1980) determine that households with college educated heads are more aware of the full life cycle costs of the vehicle ownership. People with a higher degree of education are also more likely to buy new cars [Mohammadian and Miller, 2003].

Gender is one other attribute which governs the vehicle ownership and use. In general, male drivers are more likely to drive bigger cars [Mohammadian and Miller, 2003]. Bhat and Sen (2004) in their study show that males have a preference to own pick up trucks. Age of the household head can define the vehicle ownership and use models. Manski and Sherman (1980) predict that households with heads over 45 years have a strong preference to own heavy vehicles and younger households prefer lighter vehicles.

4.2 VEHICLE CHARACTERISTICS

Operating, maintenance and capital costs play an important role in defining the vehicle type to own and the number of miles to travel for each vehicle. Only fuel cost per mile is considered as the operation costs in our model though it is only a partial indicator of the operating costs due to lack of data. Similarly, only vehicle price is considered as the capital costs even though it does not capture the depreciation rate. Maintenance costs are ignored due to unavailability of the data. As stated by Goldberg (1998) the fuel cost per mile and vehicle price are the parameters of special interest in modeling a vehicle household fleet. The former variable gives an idea of the consumer's preference for fuel efficiency and the latter can be used to derive the elasticity of substitution between various vehicle types. In general, higher operating and vehicle prices decrease the probability that a household will own any type of vehicle especially for the lower income households.

4.3 VEHICLE NUMBER CHOICE MODEL

In this model a household can choose not to own any vehicle or one, two, or three vehicles. Households owning more than three vehicles were not considered. The vehicle choice model can be represented by Equation 4-1:

$$N = f\ (I, U, HH) \tag{4-1}$$

where the number of vehicles a household chooses to own (*N*) is dependent on a number of factors, such as income (*I*), household location (*U*), and other household characteristics (*HH*).

4.4 VEHICLE TYPE CHOICE MODEL

The vehicle type model is represented by Equation 4-2:

$$T = f\,(Pv, Pm, Pv * Pm, I, U, HH) \qquad \textbf{(4-2)}$$

where the type of vehicle a household chooses to own (*T*) is dependent on a number of factors, including fuel cost per mile (Pm), the price of the vehicle (Pv), income (*I*), household location (U) , and various other household characteristics (*HH*). $Pv * Pm$ represents the interaction between the two variables. This defines the sensitivity of the household to fuel cost per mile with respect to the price of the vehicle. In theory this variable should be positive which means that when people chose to own a specific vehicle they are less elastic or less sensitive to the operating costs.

4.5 VMT MODEL AT THE HOUSEHOLD LEVEL

The VMT model is represented by Equation 4-3:

$$VMT = f\,(Pm, I, Pm * I, U, HH) \qquad \textbf{(4-3)}$$

where the total annual miles a household drives (*VMT*) is dependent on a number of factors such as fuel cost per mile (*Pm*), income (*I*), household location (*U*), and various other household characteristics (*HH*). $Pm*I$ is an interaction variable between the fuel cost per mile and income of the household. The description of the variables used in the discrete continuous choice (DCC) model is presented in Appendix A2.

5.0 DATA

The data source used for this study was obtained from the 2001 National Household Travel Survey (NHTS), sponsored by the U.S Department of Transportation and Federal Highway Administration (FHWA). This is a study that has been conducted since 1969 approximately every six to ten years which consists of the data of various modes of transportation. The earlier versions are known as the Nationwide personal transportation survey (NPTS) which focused on daily trips and the American travel survey (ATS)[1] which provides information on long distance trips. Since 1969, this data has been primarily used by various agencies and researchers to study the policy implications and travel behavior trends. This has also been the primary data source in various congestion, traffic safety, energy consumption, traffic forecasting and bike/pedestrian studies.

NHTS is a cross sectional survey, which collects data from different households at a given point of time. Discrete choice models are usually estimated using cross sectional and revealed preference surveys which are based on the individual's choice. The survey sample is drawn randomly by their telephone numbers and included household interviews, person interviews and odometer readings[2].

The 2001 NHTS consists of household, vehicle, person, daily and long distance trips[3]. The household files consists of the household characteristic data such as the income, household size, number of vehicles owned, location of the household, household head characteristics, workers, number of children, etc. The vehicle file consists of data related to each of the household's vehicles such as the annual miles driven on the vehicle, vehicle type, fuel efficiency, fuel price, etc. The person file consists of the trip, vehicle, income, education, age and other information of the individuals for each household. The daily trip and long trip files consist of the trip characteristics of each trip the person made.

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[1] 2001 NHTS is an updated version of the NPTS conducted in 1969, 1977, 1983, 1990 and 1995; and the ATS conducted in 1977 and 1995.

[2] The odometer reading for each vehicle in a household were conducted in two phases first one during the person interview and the second one after two months. These readings facilitate the estimation of the annual miles driven.

[3] The interview questions were framed to get the required information and the data was sorted out.

For the discrete continuous choice model, the data from the household and vehicle files is used. Discrete continuous choice models are data intensive and require large data sets. Oregon has 407 households, however not all households have the information regarding the vehicle characteristics. Cluster analysis was used to identify six other states similar to Oregon. These states are Colorado, Michigan, Minnesota, Utah, Virginia and Washington. There were 3353 observations after eliminating the data which did not contain the crucial variables[4].

5.1 HOUSEHOLD CHARACTERISTICS

The different household characteristics used for our analysis include the household income, location of the household, children as a percentage of the household size, the number of workers, age and gender of the household head. These characteristics play an important role in the decision of the household to own 'x' number of vehicles; income and location being the policy variables. 'HHFAMINC' in the NHTS data represents the total household income and is classified into eighteen groups. The median value of each group is assigned to each household and the incomes are divided into six groups to make up for the lack of income data in a few of the 18 groups. The six income group classification is chosen to be consistent with the Census 2000 classification and is shown in Appendix A.1. 'URBRUR' defines the location of the household if it is located in an urban area or a rural area as defined by the Census classification[5]. The 'URBRUR' variable is given a value of one if situated in an urban area and zero if rural. The NHTS data contains the information on the household size and the number of adults in each household. The number of children is derived from this. The households need for the vehicles and vehicle type depends on the children and their needs. For instance, a family might prefer to own two vehicles; probably a car and SUV to accommodate the children. The 'WRKCNT' variable gives the number of workers in a household. NHTS reports the age and gender of the respondent directly. It can be assumed that the respondent is the household head. The age groups for the households are divided into three categories: Young, if age is less

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[4] The household identification from the household and vehicle files were matched and those household missing any of the required household and vehicle characteristics was eliminated.

[5] Population density of 1000 people per square mile in the city is classified as urban and 500 people per square mile in the surrounding area as rural.

than or equal to 30 years; Middle, if age is greater than 30 and less than or equal to 60; and senior if above 60. If a person is 35 years the middle category is given a value of one and zero for the other two categories. Similarly, the gender variable is given a value of one if male and zero otherwise. The education of the respondent is used as one of the independent variables in the vehicle type and VMT model. The variable is given a value of one if the respondent has a college degree and zero otherwise.

5.2 VEHICLE CHARACTERISTICS

NHTS defines fuel efficiency for each vehicle owned by the household and also the price of gasoline per gallon. The price per gallon is divided over the fuel efficiency to obtain the fuel cost per mile. In our model, the fuel cost per mile is considered as the operating cost though it is only a partial indicator of the total operating costs of a vehicle. The 2001 NHTS data set contains information on the vehicle make and model owned by each household. The value of the vehicle in the year 2001 is considered regardless of the year it is manufactured. The vehicle prices were obtained from the 2001 Ward's automotive year book for all the available 2001 light vehicles in the U.S market according to the make and model [Wards Communications, 2001]. However, the 2001 Ward's automotive year book does not specify the prices of vehicles of outdated makes and models (e.g., Hyundai Excel which was manufactured during 1984-1994). Therefore, the households with these unavailable vehicle prices are dropped from the data set.

This might not be realistic because the lower income households tend to own old vehicles. Murakami and Young (1997) in their study observe the daily patterns of low income people and conclude that low income people do not own a car compared to higher income groups and even if they do the cars tend to be old. They also prove that people belonging to the lower income groups are less likely to use their car and use other private modes of transportation such as carpooling. It might be possible that the unavailable vehicle prices due to the outdated models belonged to those from the lower income groups and this could bias the final results. An analysis of these omitted observations showed that the maximum percentage of omitted one vehicle households belonged to the lower income groups and the maximum percentage of two and three vehicle households belonged to the higher income groups and is shown in Table 5-1. The maximum number of deleted observations belonged to the two and three vehicle households in general because only those households with all the vehicle prices are considered i.e a three vehicle household should have the vehicle prices for all the three vehicle within the household if not it is omitted from the model.

Table 5-1: Total missing observations in the vehicle type model

Income group	One vehicle households	Two vehicle households	Three vehicle households
1	26.17%	7.14%	5.64%
2	37.89%	20.06%	13.78%
3	17.58%	20.36%	16.28%
4	5.08%	19.30%	21.92%
5	5.86%	10.64%	12.94%
6	7.42%	22.49%	29.44%
Total households	256	658	479

The vehicle price here is considered as the capital costs though it does not capture the depreciation rate and consumer credit. The following section provides description regarding the usage of data for each sub model.

5.3 VEHICLE NUMBER CHOICE MODEL

The number of vehicles a household owns is included in the household file and the vehicle file of the 2001 NHTS data set. The data set is arranged for households owning no vehicles, one vehicle, two or three vehicles. The model is estimated with reference to the households owning no vehicles. The descriptive statistics for this model are presented in Table 5.2.

Table 5-2: Descriptive statistics for vehicle number choice

	Oregon	Colorado	Michigan	Minnesota	Utah	Virginia	Washington	Total
Total observations	407	466	994	681	200	737	705	**4190**
HHs with 0 vehicles	19	17	41	23	6	31	32	**169**
HHs with 1 vehicle	100	122	243	178	39	176	173	**1031**
HHs with 2 vehicles	163	183	414	272	88	296	291	**1707**
HHs with 3 vehicles	76	90	174	127	35	155	126	**783**
HHs with more than '3' vehicles	49	54	122	81	32	79	83	**500**
Final observations*								**3353**
0-vehicle HHs	18	10	34	19	6	26	24	**137**
1-vehicle HHs	90	113	212	162	39	160	160	**936**
2-vehicle HHs	154	168	371	247	78	274	264	**1556**
3-vehicle HHs	68	85	157	119	34	144	117	**724**

*The number of final observations is less than the total observations because the household income, location, and education of the household head were not reported for some households.

5.4 VEHICLE TYPE MODEL

As described earlier, vehicle type choice is a function of vehicle price, fuel cost per mile and other characteristics. In order for the household's choice between a car and truck to be captured, all vehicles are categorized into these two vehicle groups. Different categorizations were tested based on the miles per gallon a vehicle achieves, vehicle dimensions, and vehicle weight. This information was obtained from the following sources:

- NHTS Classification

The 2001 NHTS data set includes the variable 'Vehicle type' which divides the vehicle into eight categories: car, van, SUV, pickup truck, other truck, recreational vehicles, motorcycles and other. For the vehicle type choice model cars, vans and SUVs are grouped into the 'Car' category, and pickup trucks and other trucks are placed into the 'Truck' category. RV's and motorcycles are ignored, as the vehicle price data for RV's is not available. This classification seems reliable, as it is directly obtained from the NHTS data set. This approach also makes the work of arranging the data easier. However, a few discrepancies are found in the data set; for example, a Ford pickup was categorized as a van.

- MPG Classification

Vehicles are divided into 'cars' and 'trucks' based on their miles-per-gallon rating. The vehicles are classified based on the EIA adjusted fuel efficiency figures from the NHTS data set. The vehicles which have less than 20 miles per gallon are categorized as 'trucks,' and those with 20 or greater miles per gallon are categorized as 'cars.' This model displays the correct signs for most of the coefficients and they are significant when compared to the results obtained from the NHTS classification. This is the second-best model after the vehicle weight classification.

- Wards Classification

Wards Automotive year book for 2001 divided vehicles in to various subcategories.[6] Criteria for this segmentation are based on the body style, typical base price and size. For vehicles where size is a major factor in determining categorization, length is the lead determinant. Using the length criteria, the vehicles in the sample are categorized into 'small cars,' 'medium cars' and 'trucks.' All cars, including luxury and sports cars, are included under a 'cars' category and all SUVs, light trucks and heavy trucks are considered as 'trucks.' Various models are tested. This approach results in a more complicated model and thus requires a bigger data set than we currently have.

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[6] Lower small car; Upper small car; Small specialty car; Lower middle car; Upper middle car; Middle specialty car; Large regular car; Lower, middle and upper luxury car; Luxury specialty and sports car; Small and middle cross utility vehicle; Small , middle and large sport utility vehicle; Small, large and luxury vans; Small and Large pickups.

- Vehicle weight classification.

Vehicle weights are obtained for each make and model of the vehicle from the internet auto guide (*www.internetautoguide.com*). The median vehicle weight is used to categorize the vehicles into 'cars' and 'trucks'. After evaluating several models using different specifications for the above classifications, the vehicle weight classification gives better results with significant coefficients and correct signs and hence is considered for the analysis. The descriptive statistics for the vehicle type model using the vehicle weight classification is presented in Table 5.3.

Table 5-3: Descriptive statistics for vehicle type

	Oregon	Colorado	Michigan	Minnesota	Utah	Virginia	Washington	Total
One vehicle type								
Number of households owning a car	34	58	106	63	13	105	74	**453**
Number of households owning a truck	19	20	63	42	10	30	31	**215**
Total	53	78	169	105	23	135	105	**668**
Two vehicle types								
Number of households owning both cars	26	35	58	48	13	65	38	**283**
Number of households owning a car and truck	31	47	108	64	19	75	64	**408**
Number of households owning both trucks	16	17	52	21	7	24	30	**167**
Total	73	99	218	133	39	164	132	**858**
Three vehicle types								
Number of households owning all cars	1	9	10	6	1	12	6	**27**
Number of households owning all trucks	2	3	7	5	0	3	8	**34**
Number of households owning two cars and a truck	5	13	17	11	7	17	11	**75**
Number of households owning two trucks and a car	4	5	12	11	3	13	12	**68**
Total	12	30	46	27	11	45	33	**204**

5.5 VEHICLE USE MODEL

The vehicle use model is run at the household level. The NHTS data set includes the total annual miles driven by each household and also the vehicle miles for each vehicle separately. A separate VMT model is developed for each category of vehicles a household chooses to own, based on the schematic in Figure 4.1 in the previous section. The descriptive statistics for this model are presented in Table 5.4.

Table 5-4: Descriptive statistics for vehicle use

	Oregon	**Colorado**	**Michigan**	**Minnesota**	**Utah**	**Virginia**	**Washington**	**Total**
One vehicle type								
Number of households owning a car or truck	50	75	161	102	22	128	98	**636**
Two vehicle types								
Number of households owning both cars or both trucks	17	52	53	25	9	38	28	**222**
Number of households owning a car and truck	19	45	35	25	8	28	26	**186**
Total	36	97	88	50	17	66	54	**408**
Three vehicle types								
Number of households owning all cars or all trucks	1	3	4	9	2	4	2	**25**
Number of households owning two cars and a truck (or) two trucks and a car	2	3	12	6	2	11	7	**43**
Total	3	6	16	15	4	15	9	**68**

6.0 ESTIMATION AND RESULTS

Using the data described in the previous section the vehicle choice, vehicle type and VMT model are estimated using the program LIMDEP Version 9.0. The parameters of the discrete model are estimated for three alternatives (i.e., one, two or three vehicles), and the zero-vehicle condition is considered as the base alternative. The coefficients of the model indicate the propensity to own one, two, or three vehicles with positive values indicating an increase in the probability and negative values indicating a decrease in the probability. The same applies for the vehicle type and vehicle use models.

6.1 VEHICLE NUMBER CHOICE MODEL

The vehicle number choice model shows that income and location have a significant effect on the number of vehicles a household chose to own. As income increases, a household is more likely to own a vehicle. The households are also more likely to own three vehicles over two; two over one; and one over none. Similarly, a household located in an urban location is less likely to own a vehicle than a household in a rural location; and the likelihood of owning more than one vehicle decreases for households living in an urban area. This can be attributed to the fact that people living in urban areas tend to have more access to other modes of transportation such as rail or bus, compared to those in rural areas or due to the parking costs.

Household characteristics also have a significant impact on a household's likelihood of owning vehicles. As the ratio of children to household size increase, households are more likely to own vehicles. Similarly, an increase in number of workers and the presence of a male household head increases the probability of owning vehicles. Household heads belonging to a young or middle age group are less likely to own vehicles than households headed by older people. This could be due to the fact that young and middle-aged people are more active and flexible and prefer to use other modes of transportation. However, it might also depend on the life style of the people where the older drivers were accustomed to their vehicles and had them from a long time. All the values have the expected signs and are significant. The results are shown in Table 6.1.The specification and estimation equations for these DCC model are shown in the Appendix A.4.4.

Table 6-1: Estimation results for Vehicle ownership model

Dependent variable: Number of vehicles a household chooses to own Number of households = 3353			
	One Vehicle	**Two Vehicles**	**Three Vehicles**
Variable	Coefficient	Coefficient	Coefficient
Constant	1.461**	0.502**	-0.831**
I	3.922**	5.954**	6.134**
U	-0.323*	-0.761**	-1.132**
Male	0.314*	0.532**	0.714**
Child/hh size	1.171**	2.112**	1.740**
Wrkcnt	0.480**	1.463**	2.031**
Young	-1.494**	-2.172**	-2.771**
Middle	-1.173**	-1.841**	-2.072**

** Indicates statistical significance at the .05 level
* Indicates statistical significance at the .10 level

6.2 VEHICLE TYPE MODEL

The next step of the discrete continuous choice model is the vehicle type model. The results of the vehicle type model, for the one, two, and three vehicle households are shown in Tables 6.2, 6.3 and 6.4. Most of the coefficients display the correct signs and only some of them are significant because of the fewer number of observations in each model. The observations used in the vehicle type model are approximately 50 percent of the observations in the vehicle ownership model. Due to the huge drop in the sample size, a two sample't' test is conducted to validate the sample size used in the vehicle type model. The vehicle ownership model is rerun for the reduced sample size of 1730 observations and the coefficients obtained in this model are not statistically different from those coefficients of the original model with 3353 observations. The procedure and results are showed in Appendix A.3. The results for the vehicle type sub model are summarized as follows.

With an increase in the fuel cost per mile, households are less likely to own any kind of vehicle and the probability further decreases with an increase in the number of vehicles in each household. An increase in vehicle price also decreases the probability of a household to own any kind of vehicle. For households choosing to own one vehicle, the interaction variable between the operating and vehicle costs indicate that the people are more sensitive to operating costs when they chose to own that type of vehicle. This can be attributed to the fact that the highest percentage of households owning a single vehicle belong to the lower income groups as shown in Figure 1 in the appendix. On the other hand, households owning two or three vehicles are less sensitive to operating costs when they chose to own a particular type of vehicles. These values are significant only for the three vehicle households.

Higher income increases the probability of a household to own any type of vehicle. One vehicle households are likely to own a car than a truck; two vehicle households are likely to own both cars over a car and a truck; or both trucks. Three vehicle households are likely to own all cars over all trucks or, two cars and a truck; or two trucks and a car. Also, they prefer to own all trucks over two cars and a truck; or two trucks and a car. They prefer a combination of two cars and a truck over two trucks and a car.

The number of children and workers also increase the probability of households to own certain type of vehicles. The education of the household respondents also plays a role in defining the vehicle type choice of a household. An increase in the household size decreases the probability of owning smaller vehicles over the larger ones across all the vehicle type models.

Table 6-2: Results for vehicle type models – one-vehicle households

One-Vehicle households (Truck as the reference)	
Dependent variable: Type of vehicle (Car)	
Variable	**Coefficient**
Constant	-0.071
P_m	-1.216
P_r	-0.345
P_m*P_r	-0.104
I	0.329
U	0.62**
Edu	-0.35**
HHsize	0.36
Child	0.40**
Wrkcnt	0.51*

** Indicates statistical significance at the .05 level
* Indicates statistical significance at the .10 level

Table 6-3: Results for Vehicle type models – two-vehicle households

Two Vehicle households (Both trucks – TT – as the reference)	
Dependent variable: Type of vehicle (both cars – CC)	
Variable	**Coefficient**
Constant	0.651
P_m	-2.093
P_r	-0.426
P_m*P_r	0.666
I	0.612**
U	0.601**
Edu	0.585**
HHsize	-0.344*
Child	-1.038
Wrkcnt	0.409**
Dependent variable: Type of vehicle (car and truck – CT)	
Variable	**Coefficient**
Constant	0.536
P_m	-2.093
P_r	-0.426
P_m*P_r	0.666
I	0.383**
U	0.18
Edu	0.555**
HHsize	0.101
Child	-1.33**
Wrkcnt	0.119

** Indicates statistical significance at the .05 level
* Indicates statistical significance at the .10 level

Table 6-4: Results for vehicle type models – three-vehicle households

Three-Vehicle households (Two trucks and a car as the reference)	
Dependent variable: Type of vehicle (all cars)	
Variable	**Coefficient**
Constant	-0.937
P_m	-11.22**
P_r	-3.42**
P_m*P_r	4.978**
I	0.574
U	0.288
Edu	-0.433
HHsize	-0.09
Child	-0.941
Wrkcnt	0.15
Dependent variable: Type of vehicle (all trucks)	
Variable	**Coefficient**
Constant	0.868
P_m	-11.22**
P_r	-3.42**
P_m*P_r	4.978**
I	0.541
U	0.374
Edu	0.111
HHsize	0.045
Child	1.292
Wrkcnt	-0.453
Dependent variable: Type of vehicle (two cars and a truck)	
Variable	**Coefficient**
Constant	-1.08
P_m	-11.22**
P_r	-3.42**
P_m*P_r	4.978**
I	0.45
U	0.152
Edu	-0.161
HHsize	0.244
Child	-2.479**
Wrkcnt	-0.23

** Indicates statistical significance at the 5% level
* Indicates statistical significance at the 10% level

6.3 VEHICLE USE MODEL

Table 6-5 shows the results for the vehicle use model. Even though the coefficients are not significant for several of the variables, the signs do predict several possibilities. As the fuel cost per mile for a vehicle increases, households are more likely to drive fewer miles. The interaction between the income and operating costs indicate that with higher incomes people become less sensitive to operating costs when they chose to drive. People living in urban areas drive less compared to those in rural areas. Households with higher incomes and those with more workers are likely to drive more miles. Similarly, a younger person is likely to drive more miles compared to an older person. A middle aged person is likely to drive more miles compared to a younger or older person. However, this is not consistent across all the models. People living in an urban area are less likely to drive more miles. The model shows that the number of children and household size does not have a consistent effect on the number of miles a household drives.

Table 6-5: Results for vehicle use model

Dependent variable: *Annual household miles driven by a household*

	One-	**Two-vehicle**		**Three-vehicle**	
	Car or truck	**Both cars or trucks**	**Car and a truck**	**All cars or trucks**	**Two cars and a truck (or) Two trucks and a car**
Number of observations	636	222	186	25	43
Variable name	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**
Constant	5.643**	5.951**	3.486**	8.701**	7.841**
P_m	-1.044**	-1.307**	-2.324**	-0.517	-0.896
P_m*I	0.926**	0.857*	1.931**	0.337	0.218
I	2.988**	2.666**	5.364**	1.052	0.386
U	-0.151*	-0.135*	-0.07	-0.117	-0.145
Wrkcnt	0.242**	0.105**	0.1**	-0.256*	0.032
Young	0.365**	0.302**	0.04	0.718**	0.220
Middle	0.336**	0.258**	0.07	0.892**	0.426**

Italicized variables are log transformed
** Indicates statistical significance at the 5% level
* Indicates statistical significance at the 10% level

The expected total miles traveled by each household under a current gasoline tax of \$0.024 and revenue neutral VMT fee of \$0.012 proposed by the Oregon Department of Transportation is estimated separately using the following equation.

$$Miles_{gas/vmt} = \sum_{N=0}^{3} P_N \left[\sum_{T=1}^{T_N} P_T \, . \, VMT_T\right] \qquad \textbf{(6-1)}$$

Where, P_N *is* the probability of owning *N* number of vehicles, P_T is the probability owning '*T*' type of vehicle based on the vehicle number choice and VMT_T is the miles driven conditional upon the type of vehicle *T* and vehicle number choice *N*.

The change in expenditure from a gasoline tax to a VMT fee is used to calculate the welfare impacts and the consumer surplus[7] assuming a linear demand function.
Table 6-6 shows the average changes in consumer surplus, tax revenues and welfare according to the income groups and locations.

Table 6-6: Average changes in consumer surplus, tax revenue and welfare by income (\$/household) and location

Income Group	Average Change in Consumer Surplus	Average Change in Taxes paid	Average Change in Welfare
1	-\$5.86	\$2.74	-\$3.12
2	-\$5.29	\$2.57	-\$2.73
3	\$8.92	-\$5.78	\$3.14
4	-\$3.14	\$7.68	\$4.54
5	\$6.35	-\$2.33	\$4.02
6	\$7.37	-\$1.09	\$6.28
Location			
Rural	-\$7.19	\$2.14	-\$5.05
Urban	-\$1.96	\$3.77	\$1.81

The results indicate that there would be a net gain in the social welfare for the higher income groups and a net loss of \$5.05 in the social welfare for the rural group under VMT fee. The regressivity of the gas tax to the VMT fee can be compared using the Suits index[8]. This is measured using a Gini ratio. A value of -1 indicates that the entire tax burden is borne by the members of low income groups suggesting that the

[7] See Appendix A4 for definitions
[8] See Appendix for calculations

tax in regressive. A value of +1 indicates a progressive tax i.e the entire tax burden is borne by higher income groups and a value of ‘0’ indicates a proportional tax. The highly progressive tax in the U.S is the income tax and the most regressive tax is the sales and excise tax. [Suits, 1977]

The Suits index for a gasoline tax is -0.355 and for a VMT fee is -0.378 which indicates that a VMT fee is slightly regressive compared to a gasoline tax and the burden is shifted on to lower income groups. These values are slightly higher than those predicted by McMullen and Zhang (2008) in their study where the Suits index for gasoline tax is -0.176 and for the VMT fee is -0.225. As stated by West (2001) in her model, the gasoline tax is progressive over the lower income households and regressive over the higher income households making the gasoline tax as a whole less regressive. The high regressivity of both the gasoline tax and vmt fee could possibly be attributed to the omission of the households belonging to the lower income groups due to the unavailable vehicle prices.

7.0 CONCLUSIONS AND FUTURE RESEARCH

Public policies influence the mode, frequency and distribution of travel for consumers. Any policy that discourages people from buying and using vehicles, or charges fees based on miles or emissions, has potential distributional impacts. Any of these policies could induce some drivers to drive less, own one vehicle instead of two, or choose to buy a car instead of an SUV. The miles a consumer drives a vehicle depends on the type of vehicle he or she chooses to drive and also the availability of other vehicles. If the consumers are charged based on the miles driven, it might induce some to drive less or use more public transit or carpools. A family with multiple cars, who used to drive individually, might choose to travel together or carpool. Changes can be seen at both distributional and behavioral levels. This study investigates the distributional impacts of such a fee that charges the user based on the miles driven using a discrete continuous choice modeling approach. The results showed that shifting to a VMT fee of $0.012 per mile is slightly regressive compared to $0.024 per gallon gasoline tax.

The findings from this study indicate that the switch to a VMT fee would increase the social welfare for the higher income groups. There will be a net gain in the social welfare of people living in the urban areas and a net loss in the social welfare of those living in a rural area. This supports the fact that people living in rural areas travel more be it to their work places or anywhere else. These results proved similar to those developed by Nakahara (2007) using the OLS model which predicted that a VMT fee would increase the welfare of the higher income groups.

.The DCC models are data intensive and a more robust model could be developed with better data. This model was based on several assumptions especially the vehicle price data which was not directly available from the households. The DCC model could be further refined to estimate the impacts of providing a stepped VMT fee to encourage the use of fuel efficient vehicles. A stepped fee essentially provides the flexibility to provide different VMT rates for different vehicle types. A lower VMT fee could be provided to encourage the use of fuel efficient vehicles and a higher VMT fee could be imposed on the less fuel efficient vehicles.

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APPENDIX

A.1: TABLES AND FIGURES

A.1.1 Income groups

NHTS assigns households into one of 18 categories. Based on the median values of each category the income groups were reclassified in to 6 groups as shown in Table A.1.1.

Table A.1 1 Income groups categorization

Income group	Range
1	<=$14,999
2	$15,000-$29,999
3	$ 30,000-$44,999
4	$45,000-$59,999
5	$60,000-$74,999
6	$74,999-2,00,000

A.1.2: Vehicle ownership distribution according to income groups and location

A graph was plotted to better understand the vehicle ownership distribution among different income groups. Households owning no vehicles or single vehicle fall in the low income groups as expected. Multiple vehicle owning households fall in the higher income groups.

Figure A-1: Vehicle distribution according to income groups

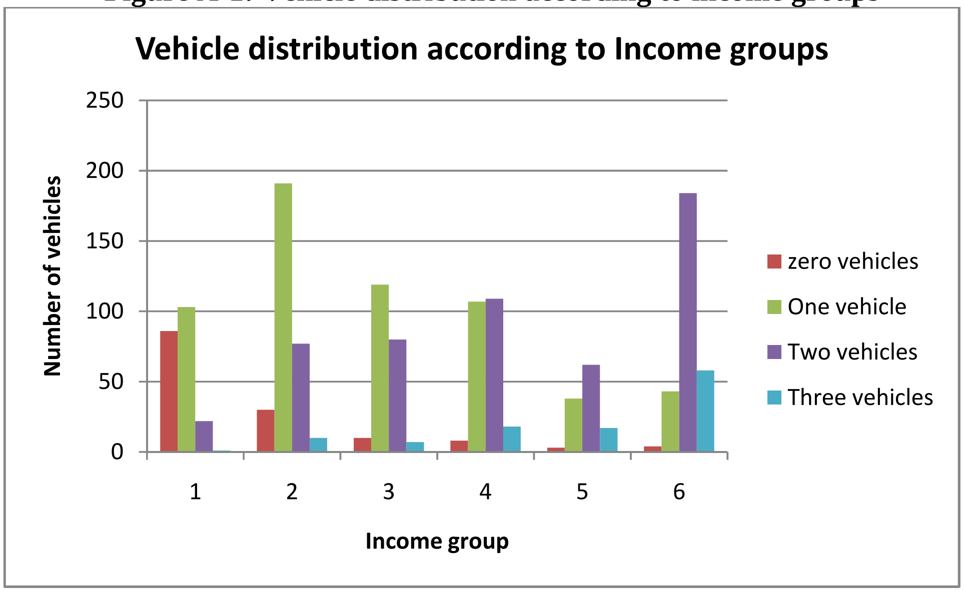
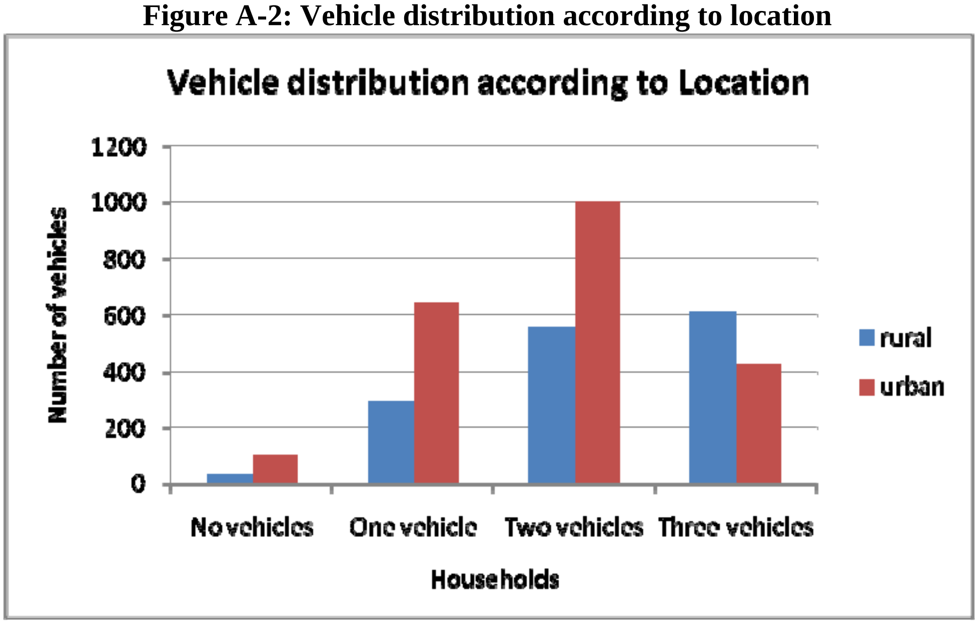


Figure A-2: Vehicle distribution according to location



A2: VARIABLE DESCRIPTION

Variable	Variable name	Description
P_m	Fuel cost per mile	Derived for each vehicle from the vehicle file of the NHTS data set. It is computed as gas cost divided by miles per gallon reported under the EIA fuel efficiency in the NHTS data set.
P_r	Vehicle price	For each make and model as given in the vehicle file of the NHTS data set, the vehicle prices were obtained from the Ward's year book 2001.
I	Income	Household annual income which is derived by taking the median value according to the category in which it falls. NHTS has 18 categories.
U	Location indicator	This value is directly obtained from the NHTS 2001 data set. Dummy variable is '1' if household is located in urban area and '0' otherwise.
Male	Gender of the Households head or respondent	Dummy Variable is '1' if the household head is a male and '0' otherwise.
HHsize	Household size	This value is obtained directly from the 2001 NHTS data set.
Child/hhsize	Children as a percentage of household size	The number of children is obtained by subtracting the number of adults (given in the NHTS data) from the household size.
Edu	Highest degree obtained by the household head/respondent	Dummy variable is '1' if the respondent has atleast attended a college and '0' otherwise. This is based on the NHTS variable for education

		1= Less than high school degree 2=High school graduate include GED 3= Vocational Technical training 4= Some college, but no degree 5= Associate’s degree 6= Bachelor’s degree 7=Some graduate or professional school but no degree 8=Graduate or professional degree
Wrkcnt	The number of workers in the household	This value is obtained directly from the 2001 NHTS data set.
Young and Middle	Age of the household respondent	The NHTS data set has an age variable. This is divided in to three categories Young (age<=30); Middle (age>30 and <=60) and Senior (age>60).
P_m * I	Interaction between fuel cost per mile and income	Allows for different elasticities for the different income groups
P_m * P_r	Interaction between fuel cost per mile and vehicle price	Allows for different elasticities for different vehicle prices.

A3: TWO SAMPLE T-TEST

A two sample t-test is conducted to test the validity of the observations used in the vehicle type model due to the reduced sample size of 1730 observations in this model compared to the 3353 observations used in the vehicle ownership model. The vehicle ownership model is run again using the 1730 observations and a two sample‘t’ test is performed.

Assuming the original sample size of 3353 as sample1 and 1730 observations as sample 2, we have two samples of unequal sizes and same variance. A two sample t-test is conducted to test for the difference in the means of the coefficients of the two samples using the following formula

$$t = \frac{X_1 - X_2}{S_{X_1X_2} \cdot \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

Where X_1 and X_2 indicate the mean of the sample 1 and sample 2 respectively

$S_{X_1X_2}$ is an estimator of the common standard deviation of the two samples. It is calculated as

$$S_{X_1X_2} = \frac{\sqrt{(n_1 - 1)S^2{}_{x_1} + (n_2 - 1)S^2{}_{x_2}}}{n_1 + n_2 - 2}$$

S_{x_1} is the standard deviation of sample 1 and S_{x_2} is the standard deviation of sample 2

n_1 and n_2 represent the degrees of freedom associated with sample 1 and sample 2.

A p-value of less than 0.05 indicates that the means of the two samples are significantly different and a p-value of greater than 0.05 indicates that they are not different. The results shown in table A.3.2 indicate that there is no significant difference between the means of the coefficients of the two samples.

Table A.3.1 shows the vehicle ownership model calculated for sample 2 with reference to one vehicle households since zero vehicle households are not considered in the vehicle type sub model.

Table A.3 1: Results for the vehicle ownership model

Dependent variable: Number of vehicles a household chooses to own Number of households = 1730		
	Two Vehicles	**Three Vehicles**
Variable	Coefficient	Coefficient
Constant	-1.123**	-3.507**
I	1.874**	2.373**
U	-0.676**	-1.61**
Male	0.161*	0.340**
Child/hh size	0.892**	0.912**
Wrkcnt	0.975**	1.689**
Young	-0.504**	-0.842**
Middle	-0.483**	-0.501**

Table A.3 2: P-values used to calculate the difference in the means

Variable	**Calculated 't'**	**P- value (two tailed)**
Income	-0.0129	0.90
Urban	-0.0881	0.93
Male	-0.0103	0.99
Child/hh size	-0.0007	0.99
Wrkcnt	0.0034	0.99
Young	-0.0021	0.99
Middle	-0.0018	0.99

A4: PROBABILITIES, ESTIMATION AND SPECIFICATIONS

A.4.1 Probabilities for vehicle choice model

$$P(0\ vehicles) = \frac{1}{1 + V1 + V2 + V3}$$

$$P(1\ vehicle) = \frac{V1}{1 + V1 + V2 + V3}$$

$$P(2\ vehicles) = \frac{V2}{1 + V1 + V2 + V3}$$

$$P(3\ vehicles) = \frac{V3}{1 + V1 + V2 + V3}$$

Where,

$$V_1 = e^{\alpha_0+\alpha_1 I+\alpha_2 U+\alpha_3 Male+\alpha_4 Chil/hhsize+\alpha_5 wrkcnt+\alpha_6 Young+\alpha_7 Middle}$$

$$V_2 = e^{\beta_0+\beta_1 I+\beta_2 U+\beta_3 Male+\beta_4 Chil/hhsize+\beta_5 wrkcnt+\beta_6 Young+\beta_7 Middle}$$

$$V_3 = e^{\gamma_0+\gamma_1 I+\gamma_2 U+\gamma_3 Male+\gamma_4 Chil/hhsize+\gamma_5 wrkcnt+\gamma_6 Young+\gamma_7 Middle}$$

Where α , β and γ represent the estimated coefficients for the one vehicle, two vehicle and three vehicle households respectively.

A.4.2 Probabilities for vehicle type model

$$P(1veh)_{car} = \frac{V_{car}}{1+V_{car}} \quad ; \quad P(1veh)_{truck} = \frac{V_{truck}}{1+V_{truck}}$$

Where:

$$V_{car=}\ e^{(\alpha_0+\alpha_1 P_m+\alpha_2 P_r+\alpha_3 P_m P_r+\alpha_4 I+\alpha_5 U+\alpha_6 Edu+\alpha_7 HHsize+\alpha_8 Child+\alpha_9 Wrkcnt)}$$

$$V_{truck} = e^{(\beta_0+\beta_1 P_m+\beta_2 P_r+\beta_3 P_m P_r+\beta_4 I+\beta_5 U+\beta_6 Edu+\beta_7 HHsize+\beta_8 Child+\beta_9 Wrkcnt)}$$

$$P(2veh)_{cars} = \frac{V_{cars}}{1+V_{cars}+V_{car\&truck}+V_{trucks}}$$

$$P(2veh)_{cars} = \frac{V_{car\&truck}}{1+V_{cars}+V_{car\&truck}+V_{trucks}}$$

$$P(2veh)_{cars} = \frac{V_{trucks}}{1+V_{cars}+V_{car\&truck}+V_{trucks}}$$

$$V_{cars} = e^{(\alpha_0+\alpha_1 P_m+\alpha_2 P_r+\alpha_3 P_m P_r+\alpha_4 I+\alpha_5 U+\alpha_6 Edu+\alpha_7 HHsize+\alpha_8 Child+\alpha_9 Wrkcnt)}$$

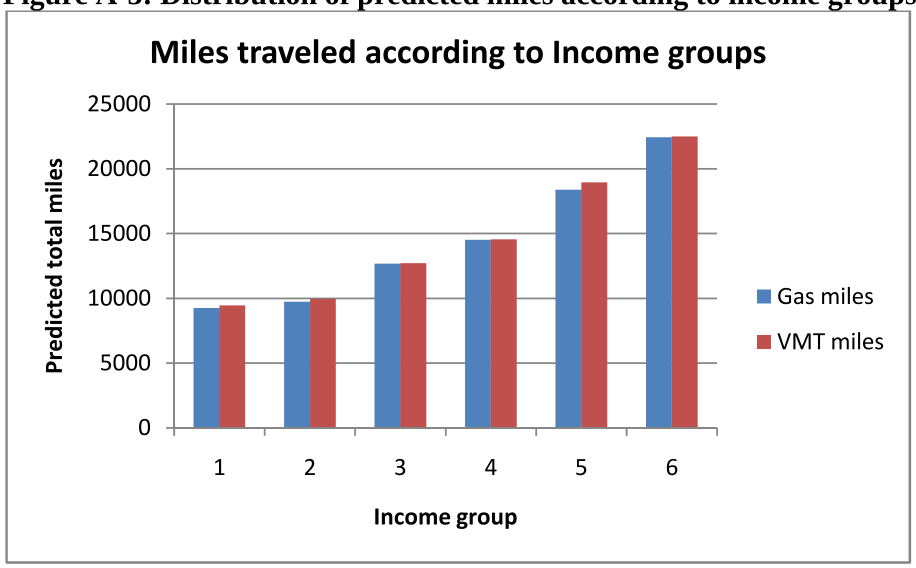
$$V_{car\&truck} = e^{(\beta_0+\beta_1 P_m+\beta_2 P_r+\beta_3 P_m P_r+\beta_4 I+\beta_5 U+\beta_6 Edu+\beta_7 HHsize+\beta_8 Child+\beta_9 Wrkcnt)}$$

$$V_{trucks} = e^{(\gamma_0+\gamma_1 P_m+\gamma_2 P_r+\gamma_3 P_m P_r+\gamma_4 I+\gamma_5 U+\gamma_6 Edu+\gamma_7 HHsize+\gamma_8 Child+\gamma_9 Wrkcnt)}$$

The same approach is followed in calculating the probabilities of three vehicle households.

A.4.3 Predicted miles for the vehicle use model

Figure A-3: Distribution of predicted miles according to income groups



A.4.4 Specification and Estimation equations

The specification for the vehicle ownership model can be represented as

$$V_n = \alpha_0 + \alpha_1 I + \alpha_2 U + \alpha_3 male + \alpha_4 child / hhsize + \alpha_5 wrkcnt + \alpha_6 young + \alpha_7 middle$$

The specification for a the vehicle type model for a one vehicle households can be represented as

$$V_{miles\,(n)} = \beta_0 + \beta_1 P_m + \beta_2 P_m * I + \beta_3 I + \beta_4 U + \beta_5 child + \beta_6 hhsize$$
$$+ \beta_7 wrkcnt + \beta_8 young + \beta_9 middle$$

$$V_{truck} = \alpha_1 P_{m-truck} + \alpha_2 P_{r-truck} + \alpha_3 P_{m-truck} * P_{r-truck}$$

The specification for the continuous model can be represented as

$$V_{miles(n)} = \beta_0 + \beta_1 P_m + \beta_2 P_m * I + \beta_3 I + \beta_4 U + \beta_5 wrkcnt + \beta_6 young + \beta_7 middle$$

The values from the estimated model can be substituted to interpret the equations. For example, considering the vehicle use model for single vehicle households after substituting the values, the equation can be represented as

$$V_{miles(n)} = 5.643 - 1.044 P_m + 0.926 P_m * I + 2.998 I - 0.151 U + 0.242 wrkcnt + 0.365 young$$
$$+ 0.336 middle$$

1 percent increase in the fuel cost per mile causes a 0.48 percent decrease in the miles traveled by a household. The miles driven by a urban household are only 86 percent of those driven by a rural household.

In a similar manner, all the other equations for both the discrete and continuous sub models can be interpreted.

A5: CONSUMER SURPLUS, REVENUE AND WELFARE

Total surplus which is the sum of consumer surplus and producers surplus is a measure of social wellbeing and is used to evaluate the efficiency of a policy. The producer's surplus here is the change in tax revenue under a VMT fee. The welfare is estimated assuming a linear demand function.

The consumer surplus can be represented as follows

$$CS = \sum_{N=0}^{3} P_N^A \left[\sum_{T=1}^{T_N} P_T^A \left\{0.5(P_m^B - P_m^A)(VMT^A + VMT^B)\right\}\right]$$

Where, P_m^B is the fuel cost per mile under the gas tax.

It is calculated as: $\frac{Gas\ cost}{Miles}$

P_m^A is the fuel cost per mile under the VMT fee.

It is calculated as: $\frac{(Gas\ cost - 0.24)}{Household\ average\ fuel\ efficiency} + 0.012$

Where:

P_N is the vehicle number choice

P_T is the vehicle type choice

VMT^A is the vehicle miles traveled under the VMT fee

VMT^B is the vehicle miles traveled under the gasoline tax

The difference $(P_m^B - P_m^A)$ determines the sign of the change. If the fuel cost per mile under the VMT (P_m^A) fee exceeds the fuel cost per mile under the gasoline tax (P_m^B), we expect a reduction in the total miles traveled and also in the consumer surplus. Similarly, if the fuel cost per mile decreases under the new policy, we expect the households to drive more thereby increasing the consumer surplus and welfare as a whole.

Revenue collected under the gas tax is calculated as:

(1) Revenue (Gas) $= \frac{0.24}{Household\ \ fuel\, efficiency} \times$ Predicted miles under the gasoline tax

(2) Revenue (VMT fee) = 0.012 × Predicted miles under the VMT fee

Revenue collected by the state agency for each household is obtained by the revenue collected under the gasoline tax from the revenue collected under the VMT fee.

A6: SUITS INDEX

A Suits index is a value used as a measure to predict the regressivity of a tax. It is related to the Gini ratio and is calculated by comparing the area bounded by the Lorenz curve and the proportional line drawn at 45 degrees. Points on the 45 degree line indicate a proportional tax; points falling above the 45 degree line suggest a regressive tax and points below it represents a progressive tax. The graph is plotted by calculating the accumulated percentage of total tax against the accumulated percentage of total income.

Daniel B Suits [1977] gives the following formula to calculate the suits index

$$S = 1 - \frac{1}{K}\int_{0}^{100} T(Y)dy$$

Where K represents the area of the triangle under the curve or above the diagonal line and K=5000

$$\int_{0}^{100} T(Y)dy = \frac{1}{2}\sum_{i=0}^{n}\{[T(y_i) + T(y_{i-1})](y_i - y_{i-1})\}$$

n represents the number of discrete points and *n*= 6 , as there are 6 income groups in this study

y_i is the accumulated income on the x-axis

$T(y_i)$ is the accumulated percent of total taxes paid and is represented on the y-axis.

Figure A-4: Suits Index for Gasoline tax

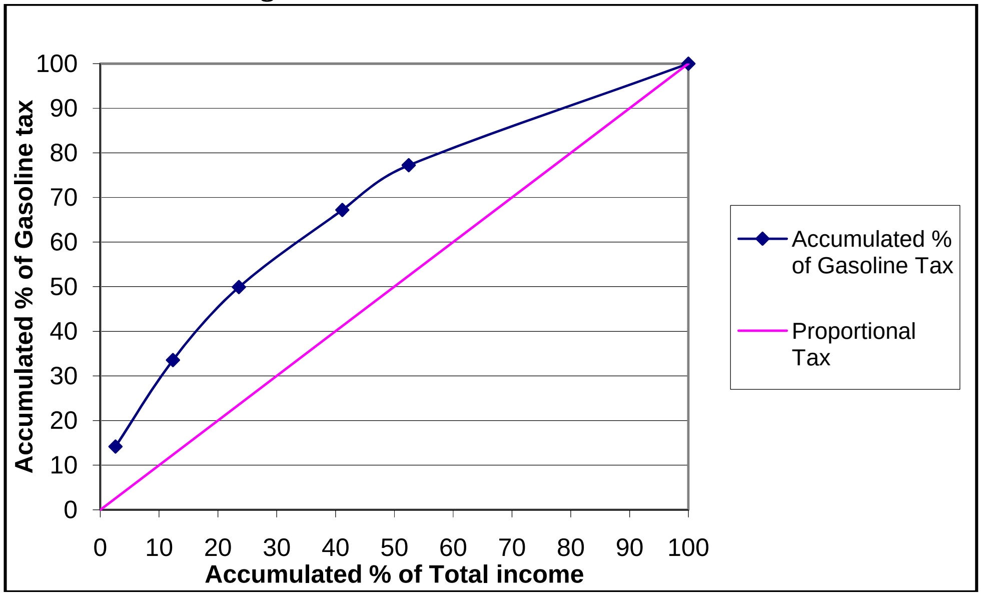


Figure A-5: Suits index for VMT fee

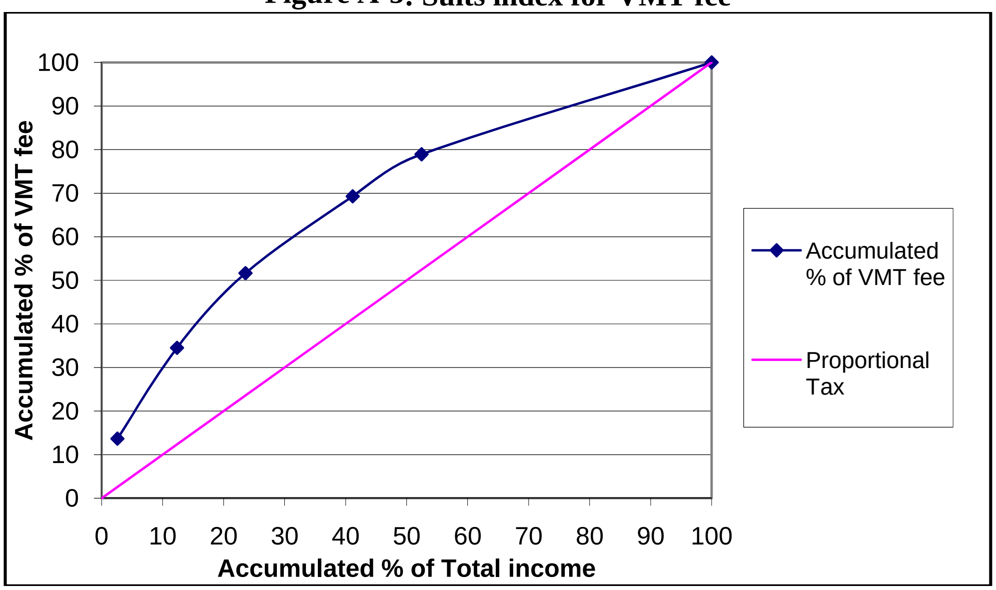


Table A.6 1: Values used to calculate Suits index

Income group	**Accumulated income (%)**	**Accumulated gas tax (%)**	**Accumulated VMT fee (%)**
1	2.594	14.159	13.666
2	12.361	33.546	34.509
3	23.582	49.909	51.633
4	41.166	67.196	69.276
5	52.443	77.221	78.915
6	100	100	100
Suits Index		-0.3555	-0.37785