Estimating Impacts of a Vehicle Mile Tax on Oregon Households

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Oregon's gasoline tax no longer serves as an economically efficient revenue source due to increasing fuel efficiency and the emergence of alternative fuels. In response to this problem, the Oregon Department of Transportation is exploring alternatives to the gasoline tax. Among the most promising alternatives is a flat-rate vehicle mile tax. Critics argue that a flat-rate fee will discourage the purchase of fuel efficient vehicles and may impact social groups differently, placing a heavier burden on lower income and rural households. This paper estimates the socio-economic impacts of the proposed policy based on income and location using an Ordinary Least Squares (OLS) and Three-Stage-Least Squares (3SLS) model and Oregon data from the 2001 National Household Travel Survey. Suits Indices indicate both the gasoline and VMT taxes are, overall, regressive. The OLS model suggests the VMT fee will be more regressive than the gasoline tax, while the 3SLS model suggests the VMT fee will be slightly more progressive than the gasoline tax. The overall impact of a policy shift depends largely the model specification chosen. Furthermore, the 3SLS results appear to be consistent with public concerns. The average household will reduce its average fuel efficiency, however, the reduction in annual miles driven may offset some of the environmental concerns.

Master of Science thesis of Kyle S. Nakahara presented on September 19, 2007.

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Kyle S. Nakahara, Author

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1. Introduction

Oregon's gasoline tax revenues - the primary revenue source for transportation projects - are no longer an economically efficient source of revenue. Oregon has not seen an increase in the state gasoline tax since 1993, despite rising inflation. Voters have repeatedly rejected initiatives proposing tax increases. Parry and Small (2005) find the optimal gasoline tax in the United States should be more than double the current tax[1]. Despite the fact that vehicle miles traveled (VMT) per capita has been relatively constant over the years, the state's population is expected to increase by 41 percent by 2030[2], thus increasing overall miles driven and road wear (Oregon Transportation Plan, 2006).

The Oregon Department of Transportation (ODOT) is currently exploring alternatives, specifically a VMT fee[3], to replace the gasoline tax. It may be helpful to note here the difference between a tax and a user fee. A user fee implies that a fee will be imposed on only those who use - in this case - the roads and in turn the revenues collected will be used solely for the roads from which the fees were collected. Tax revenues on the other hand can be redistributed to other programs (Kulash, 2001). Since the creation of the Highway Trust Fund, gasoline tax revenues have been set aside for the upkeep of highways and other roads however, drivers are not necessarily paying for their

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[1] According to Parry and Small (2005), in 2000 the average gasoline tax - which includes both the federal and state tax - was approximately \$0.41 (measured in 2001 dollars). Their estimated optimal gasoline tax for the United States, which accounts for pollution, congestion and accidents was approximately \$1.04 in 2001 dollars. These adjustments are based on the Consumer Price Index inflation calculator.
[2] According to the 2000 Census.
[3] Throughout this paper I will be using 'VMT fee'and 'distance-based user fee' interchangeably.

individual road use. Those with fuel inefficient vehicles end up paying more than their share of road damage.

A pilot study is currently being conducted in the Portland area to test the feasibility of a new technology. On-board devices are installed in each vehicle and using Global Positioning Satellite - Automatic Vehicle Identification (GPS-AVI) technologies miles can be tracked and priced based on distance and geographic location. The technology would allow for a relatively flexible rate structure. Thus, it would be possible to set different prices for urban or rural areas, different income groups, time of day, residential or highway roads, road types, fuel efficiency or vehicle type (size for example).

There are concerns of feasibility and equity with the proposed change from a gasoline tax to a vehicle mile user fee. ODOT is proposing a phase-in period of approximately twenty years, assuming that around five percent of the vehicle fleet in Oregon is replaced every year. Retro-fitting vehicles leads to an increased risk of evasion or tampering with devices and is also significantly more expensive. Instead, new vehicles sold in the state will be equipped with the appropriate technology and will pay a VMT fee while drivers with older vehicles will continue to pay the gasoline tax (Whitty, 2006).

Two issues stand out. First, critics argue that a flat-rate VMT fee discourages fuel efficiency and drivers should therefore be compensated in some way. However, lower income households tend to own fuel inefficient vehicles (West, 2002). From an equity stand point, this may alleviate some of the burden on lower income households. Second, those living in rural areas tend to drive more miles than their urban counterparts. Rural households face fewer options when it comes to day-to-day trips (for example, a trip to the grocery store) since there are in general fewer businesses in rural areas. Someone living in an urban area, on the other hand, will have the option of reducing miles driven once the new policy is enforced. They may choose to shop at a closer grocery store, for example. If families in rural areas suddenly have to pay per-mile, they will be less likely to change their behavior (more inelastic demand for miles) and will consequently be negatively impacted.

Using household level data from the 2001 National Household Travel Survey, this paper will help to quantify the impacts of the proposed policy on different income groups as well as those in different areas (urban versus rural). Data was available for each vehicle owned by a household and weighted averages of household fuel efficiency[4] were calculated to predict this policy's impact on household miles and car choice (based on average fuel efficiency).

This paper is structured as follows. Section two provides a summary of road pricing theory. Section three outlines previous work on measuring distributional impacts of a gasoline tax and a distance-based user fee. Section four describes the methodology used in the estimation process. Section five describes the data used in the estimation. Section six presents results from the estimation and section seven concludes.

[4] Weighted by miles driven on each vehicle.

2. Theory

This paper quantifies the impacts of a VMT fee, which is a user-based fee. A user fee, contrary to a tax, is paid by those who use a facility or service and the funds are then used for the maintenance and improvement of that facility or service. A tax, on the other hand is not necessarily based on use and its revenues can be redistributed to benefit a third party (Kulash, 2001).

Vehicles today are incredibly diverse in terms of fuel type (hybrids, gasoline or diesel powered) and size, and both of these attributes play a large role in terms of how much each driver actually pays in gasoline taxes. For example, consider a hybrid vehicle with 40 MPG and a sedan with 25 MPG. These two vehicles will likely share quite similar physical characteristics and are expected to cause the same amount of road damage based on those physical characteristics. However, since the hybrid vehicle has such a high fuel efficiency, the driver of this vehicle will pay less under the gasoline tax than the driver of the sedan. Said another way, if both drivers purchase one gallon of gasoline from the same gas station, the driver of the hybrid vehicle will get 40 miles out of that purchase, while the driver of the sedan will get only 25 miles at the same price. Given that our objective is to cover road damage costs, this is an economically inefficient situation in that those with fuel inefficient vehicles are overburdened with gasoline taxes.

When first introduced, the gasoline tax served as an efficient way of allocating road wear costs; vehicles in the early 1900s were not as diverse as they are today. The large diversity in fuel efficiency - the main determinant of the amount drivers pay in gasoline taxes per mile - has led to inefficiencies in road wear cost allocation. Furthermore, there is an upward trend in fuel efficiency. As vehicles become more fuel efficient, drivers pay less in gasoline taxes per mile.

Total social costs include both private and public costs. Private costs include car insurance, maintenance costs and repair costs. Public costs include road use and externalities such as congestion and pollution. Road use fees are paid to the government and are used to maintain and improve roadways. These are primarily collected through the gasoline tax. Road wear costs can be explicitly estimated, however, the collection process can be difficult to implement. External costs, such as congestion, are often difficult to measure and price. This paper ignores these externalities, however, it is possible to vary the VMT fee to account for these externalities.

Under current circumstances, it is likely drivers pay disproportional amounts of their public costs when we consider road wear costs; those with fuel efficient vehicles pass some of the burden on to those with fuel inefficient vehicles. Furthermore, gasoline taxes across the United States have been relatively stagnant over the past decade, despite rising inflation. Parry and Small (2005) compare gasoline taxes in the United States to those in Britain and find that gasoline taxes (federal and state) in the United States are far below the efficient tax level, suggesting that people drive far more than they ought to because the ‘price’ of driving is too low. This leads to more wear and tear and also higher congestion.

From an economic theory standpoint, it should be the case that marginal social cost equals marginal social benefit. Social costs - public costs and other externalities - in this case would include the damage imposed on roads, added traffic congestion, noise and emission pollution. Benefits would include the value received from driving. It would be cost prohibitive to measure and charge a fee exactly equal to an individual driver's marginal social cost, however different policies can bring society closer to an economically efficient outcome. While the gasoline tax is an effective tax on emissions[5], a VMT fee is a more effective way of reducing traffic congestion and

[5] West (2002) states that emissions are proportional to fuel use.

accidents by giving people the incentive to reduce miles driven (West, 2002). In this sense, a VMT fee would be closer to the economically efficient outcome, where drivers pay a price closer to the marginal damage imposed on other drivers and on the roads than under the current gasoline tax. If drivers are made explicitly responsible for their contribution to road and environmental damage, it should be the case that drivers will reduce total annual miles, taking only the trips with the greatest value to them (Small et al., 1989).

We need both a demand and supply, or cost, function to estimate the efficient user fee that will maximize total surplus (and thus create an efficient market) under uncongested traffic flows. Road pricing theory often considers congestion externalities as well as road wear (Small et al., 1989 and Button, 2004). Our study does not address congestion pricing and will be different from these models. Small (1989) and Button (2004) both include value of time along with road costs as their total cost function when estimating the optimal congestion tax. This presents a few problems in our model. First, we lack data on a household's value of time and second, since ODOT is not yet considering a congestion fee, it may be more appropriate to exclude this from our theoretical model.

Our focus is on the demand for miles traveled. The following sections describe how the demand function was estimated. We do not actually estimate a cost function. Rather, we use the $0.012 per mile fee proposed by ODOT, which we assume affects households' demand for miles in the form of a change in the fuel cost per mile. We also assume road damage is a function of miles driven, which does not depend on externalities such as congestion or emissions. From this we can calculate the change in households' quantity demand for vehicle miles.

3. Previous Studies

Though this paper focuses on the impact of a distance-based user fee, this section also includes work on the impacts of gasoline taxes. Current road user fees are primarily collected in the form of a gasoline tax. Thus, we want to first estimate the impact of the current gasoline tax on Oregon households, then compare these effects to those under the proposed VMT fee. The theoretical modeling of the two are quite similar particularly because authors will often incorporate a fuel cost per mile variable in their estimation. For a representative household, the policy itself should not matter. Rather, the household responds to the fuel cost per mile for each vehicle, which can vary as a result of a change in the fuel price or the fuel efficiency of the vehicle. We use the fuel cost per mile to introduce the new policy in our model. All studies reviewed suggest that a gasoline tax and VMT fee are regressive and depending on variables included and how they are measured, the regressivity of the tax will vary. Poterba (1990) argues that using household expenditures produces more realistic results than household income. When using household expenditures, he finds the gasoline tax to be less regressive than estimated using household income. West (2002) and Walls and Hanson (1999) find a mileage-based environmental tax to be regressive. West's findings support Poterba's claim that household expenditures produces less regressive results. Walls and Hanson (1999) compare different measures (lifetime income, annual income and annual expenditures) and find, like Poterba, the regressivity of the tax varies, depending on the measure of income used. Whether the studies include households with zero vehicles or not also affects the tax's regressivity. We exclude households with zero vehicles because we are interested in the impact on current road users. Households with zero vehicles will not be (directly) impacted by this policy change[6].

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[6] It may be the case that they are better or worse off as a result of indirect impacts, such as an increase in public transit ridership, however we are not considering these impacts.

West (2002) and Walls and Hanson (1999) study the distributional impacts of an emissions tax through a VMT fee. An ‘optimal’ emissions tax on any particular vehicle would be equal to the cost of all pollutants released by that vehicle. However, this would be technologically impossible to implement. West uses the 1997 Consumer Expenditure Survey (CES) as her main data source and uses household expenditures rather than household income, arguing that households will smooth their consumption over time. Poterba (1990) also uses household expenditures (to calculate the regressivity of a gasoline tax). Walls and Hanson use the household's estimated lifetime income rather than annual income because, as they argue, households base their decisions on the income they expect to make over a lifetime, rather than their current income. West argues that reported annual household income tends to be inaccurate and therefore biased.

West uses a discrete-continuous choice model proposed by Dubin and McFadden (1984) to estimate California households' car choice and miles demanded. Miles driven is a derived demand through the use of a durable good, which in this case, is the vehicle. The Dubin and McFadden model first estimates the demand for the durable good, and given the vehicle choice, households will choose how many miles to drive. This model is able to capture the simultaneity between vehicle choice and miles driven. West's study differs from other studies in that it also includes households with zero vehicles. Since lower-income households do not own vehicles, they will not be impacted by any vehicle-related tax and the overall impact of a tax is therefore less regressive than previously suggested. Like West, Poterba's findings suggest the (gasoline) tax is not as regressive as previously estimated when households with zero vehicles are included. West also allows the demand elasticity for miles driven to vary by income groups, to “allow for the possibility that poor and wealthy households behave differently in response to increases in driving costs." This is a major departure from the other studies reviewed in this paper, which assume that households in different income groups will respond in the same way to a change in the fuel cost per mile. Our model also assumes households in different income groups will respond differently to changes in the fuel cost per mile.

West (2002) and Walls and Hanson (1999) use the Suits Index as a measure of regressivity of a VMT fee on emissions. West calculates the Suits Index to be -0.193, while Walls and Hanson calculate the Suits Index to be -0.24. A value of -1 implies perfect regressivity. These values appear to be consistent with the theory that households who do not own vehicles tend to be in the lower income groups and thus, by excluding these households from the study, taxes appear to be more regressive.

Bento et al. (2005) use the 2001 NHTS data set to estimate the optimal gasoline tax. They also use a discrete-continuous choice model to capture the simultaneity between vehicle choice and miles driven. Unlike West, the authors do not allow the elasticity of demand for miles to vary with income. According to the authors, the overall impact of a change in the gasoline tax depends on how the revenues are reallocated. The authors consider two alternatives - the tax revenues can be redistributed evenly to all drivers or the revenues can be reallocated based on income. If all drivers receive the same amount of money, the burden will be placed on those with the lowest demand elasticity - or those with an inelastic demand for miles.

4. Methodology

Simply adjusting households' fuel cost per mile and recalculating the total incidence paid per household may produce inaccurate results if we do not allow miles to vary. We calculated incidences in a static model, where we assume annual households miles do not vary as a result of a price change and found, not surprisingly that total fuel expenditures do not change much[7]. The variation in total expenditures depends solely on vehicles' fuel efficiency in the static model. Thus, the total change in tax revenue - calculated as total taxes collected under the proposed VMT fee minus total taxes collected under the gasoline tax - will equal the change in expenditures[8].

Table 1: Average Change in Tax Revenue by Location ($/Household) – Static Model Results

Location	Number of Households	Change in Revenue
Rural	108	-13.60
Urban	256	2.03

According to the static model, rural households will benefit, relative to urban households. When divided into income groups, the lowest two income groups and Income Group 4 pay more under the VMT fee than under the current gasoline tax. The fifth income group will benefit the most under the VMT policy. Thus, it appears – according to the static model – that the new policy will be more regressive than the current gasoline tax.

[7] See A6 and A7 in the Appendix for more details.
[8] Later in this paper, we estimate the change in consumer surplus and total welfare based on the OLS and 3SLS regressions, however, this is not possible with the static model since miles driven do not vary.

Table 2: Average Change in Tax Revenue by Income ($/Household) – Static Model Results

Income Group	Number of Households	Change in Revenue
1	39	7.81
2	75	5.19
3	65	-4.40
4	62	0.23
5	40	-25.24
6	67	-6.00

Economic theory suggests that as the price of a good increases (in this case, the price of driving a mile), the quantity demanded will decreases (households will drive fewer miles). By running a regression, we can calculate the changes in household miles given a change in any independent variable - in this case, a change in the fuel cost per mile.

Furthermore, all previous studies cited in this paper agree there is an endogenity problem between vehicle choice and miles driven. Researchers use different model specifications to account for this problem; a simple Ordinary Least Squares (OLS) model can incorporate a dummy variable to capture this effect, while a simultaneous equation model (SEM) can simultaneously estimate multiple endogenous variables. Another approach - the discrete-continuous choice model - first estimates the discrete vehicle choice then estimates the continuous miles demanded taking the vehicle choice as given. The models used in our empirical estimation are all based on continuous endogenous variables. This paper will therefore not address the discrete-continuous model in detail[9].

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[9] For model specification details of the discrete-continuous choice model, see Dubin and McFadden (1984).

An SEM is more appropriate than an OLS model when there are ‘feedback relationships’ between the dependent and independent variables (Gujarati, 2006). In the context of our problem, the OLS model assumes household miles have no effect on the average fuel efficiency of a household. However, there is reason to believe that while average household fuel efficiency affects total household miles, the number of miles a household drives also affects the average fuel efficiency of all vehicles[10]. For example, the number of miles a household drives depends on the types of cars a household owns, but the types of cars a household owns depends on how many miles the household expects to drive[11]. Our fuel efficiency dependent variable is calculated as a weighted average for each household, based on the miles driven for each vehicle.

Estimating annual household miles without accounting for these relationships may lead to biased results (Gujarati, 2006). That is, the estimated parameters in the OLS model may be biased. Nonetheless, the OLS model provides some interesting insight.

4.1 Ordinary Least Squares Model

The Ordinary Least Squares (OLS) model assumes annual household miles have no effect on the average fuel efficiency of the household's vehicles. Theoretically, we know this to be a false assumption. We address the relationship between household miles and vehicle type by including a substitution dummy variable equal to one if the household has more than one type of vehicle and zero otherwise. The inclusion of this

[10] Various factors, such as weather conditions and traffic conditions, will affect the fuel efficiency of any particular vehicle (U.S. Department of Energy). However, when I refer to changes in average household fuel efficiency, I am referring to the choice of vehicles (high or low MPG), not these marginal variations.

[11] Greene et al. (1999) use a 3SLS model to estimate the rebound effects caused by an increase in the overall average fuel efficiency. Small and Van Dender (2006) also estimate the rebound effect with a 3SLS model, but use fuel intensity, measured as the inverse of MPG. West (2002) uses a discrete-continuous choice model, which incorporates the discrete choice of choosing vehicle bundles (incorporating MPG) and the continuous choice of how many miles to drive, taking vehicle choice as given.

variable also allows us to calculate different elasticities for households with multiple vehicle types, and those without. Households with multiple vehicle types are expected to be less responsive to fuel cost per mile changes since they are able to substitute away from vehicles with a higher fuel cost per mile.

Our OLS model is based on the following equation:

$$M = f(P_M, I, P_M * I, U, C, SUB, P_M * SUB, \overrightarrow{HH}_M) \quad (1)$$

Where M is the total annual miles driven by the household, P_M is the fuel cost per mile under the gasoline tax, I is annual household income, U is a dummy variable equal to one if the household is located in an urban area, and zero otherwise and C is the number of vehicles the household owns. SUB is a dummy variable that takes the value of one if the household has more than one type of vehicle such as a car and truck and zero otherwise, $P_M * I$ is an interaction term between the fuel cost per mile and income and similarly P_M *SUB is an interaction term between the fuel cost per mile and the substitution dummy variable. $\overrightarrow{HH}_M$ is a vector of household characteristics that includes the number of children (CHILD), number of workers (WORK) and a dummy variable that takes the value of one if the household respondent is male and zero otherwise (MALE).

As the fuel cost per mile increases, we expect households to reduce miles driven so the coefficient on the average fuel cost per mile should be negative. Assuming miles driven is a normal good, we expect the sign on income to be positive, suggesting that as household income increases, they are able to spend more of their income on miles. We expect the coefficient on the location variable to be negative, which would imply that households in urban areas drive less than those in rural areas due to shorter commutes to work and more developed surroundings. If households have more than one vehicle, they are more likely to drive more miles. Households with multiple types of vehicles are able to substitute between vehicles as other variables, such as the fuel cost per mile. This flexibility may encourage them to drive more, relative to other households that are not able to substitute between vehicles. As the number of children or the number of workers increase, we would expect households to drive more out of necessity. Households may have to take their children to more activities, increasing miles traveled (West, 2002). West finds that male-headed households drive more miles than those headed by females. West also states that, “Male-headed households are even more likely to own two vehicles than they are to own one[12]."

The interaction term between the fuel cost per mile and income allows for different impacts on different income groups. In this case, we would expect households with a higher income to drive more miles than those with lower income as the fuel cost per mile increases because those in the higher income groups will not feel as great a burden on their total income when the fuel cost per mile changes. (That is, those in higher income groups are expected to have a more inelastic demand---as demonstrated by West.) Similarly, the interaction term between the fuel cost per mile and the substitution dummy variable allows for different impacts on those with multiple vehicle types and those without. Presumably, households with multiple vehicle types are able to substitute between their vehicles, and the coefficient should therefore be positive. That is, relative to households who cannot substitute between vehicle types, as the fuel cost per mile increases, households with multiple vehicle types are more likely to drive more miles.

The OLS regression was run on household annual miles with the fuel cost per mile under the gasoline tax[13]. The change in policy was captured by subtracting the $0.24 tax out of the gasoline price, dividing the remaining net gas cost by the fuel efficiency

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[12] Our data support West's statement. The correlation coefficient between our male dummy variable and vehicle count variable was approximately 0.16. Though not particularly high, there was a positive correlation between the two variables.

[13] See A2 in the Appendix for the calculation of fuel cost per mile.

and then adding the $0.012 mile tax[14]. The new fuel cost per mile - under the VMT fee - is thus different for every household, unless the household has an average fuel efficiency equal to 20 MPG[15]. The incidence calculations in Section 6 compare the fitted values from the OLS regression and the recalculated fitted values under the new fuel cost per mile variable, based on the estimated parameters from the OLS regression.

4.2 Simultaneous Equation Model

The data used in this study are limited to 248 Oregon households in 2001. The Simultaneous Equation Model (SEM), which incorporates all continuous dependent variables, is less data-intensive than the discrete-continuous model and is used here to estimate Oregon household vehicle ownership and vehicle usage. We use the household weighted average fuel efficiency as a proxy for vehicle choice. This can be more explicitly modeled in the discrete-continuous model.

We do not use the fuel cost per mile variable as defined in the OLS model because it is a weighted average based on household miles driven and each vehicle's MPG. Attempting to use the fuel cost per mile as defined in the OLS model complicates the incidence calculation and does not fully capture the endogeneity between household MPG and household miles. Rather, we replace the OLS fuel cost per mile with the household MPG[16].

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[14] Empirical studies show that nearly the entire state gasoline tax burden is placed on the consumer, which justifies subtracting the entire $0.24 tax from the gasoline price (Chernick and Reschovsky, 1997 and Chouinard and Perloff, 2003).

[15] ODOT based the $0.012 per mile fee on the assumption that the average fuel efficiency of all vehicles is 20 MPG; the rationale being that the average household should be unaffected by the policy change. In this case, we use the change in fuel expenditures as a measure of well-being.

[16] We can do this because we are using natural logs. This approach requires some extra work in the incidence calculation, which is described in greater detail in the Appendix.

Our SEM is based on the following equations:

$$C = f(LNHHMPG, I, U, WORK) \tag{2}$$

$$LNHHMPG = g(C, M, I, U, HHSIZE) \tag{3}$$

$$M = h(C, LNHHMPG, I, U, LNHHMPG * I, CHILD) \tag{4}$$

Where C is the number of vehicle owned by the household, $LNHHMPG$ is the weighted average fuel efficiency for the household, weighted by the miles reported for each vehicle by the household. Similar to the OLS model, we use income (I), a location dummy variable equal to 1 if the household is located in an urban area and 0 otherwise (U), number of workers in the household (WORK) and the number of children (CHILD). We also include the number of household members (*HHSIZE*). The weighted average fuel efficiency, *LNHHMPG* is used as and should be interpreted as the fuel cost per mile in the miles equations.

In the count equation, as income increases, households are able to purchase more vehicles, and the sign of its coefficient is therefore expected to be positive. Urban households are expected to own fewer vehicles relative to rural households; urban households have access to more transportation options and do not need as many vehicles. The average household fuel efficiency is expected to be inversely related to the number of vehicles. If a household increases its average fuel efficiency, it should have less of an incentive to diversify its vehicle fleet. In other words, if a household decreases its fuel efficiency, there may be an incentive to diversify and buy more vehicles to allow for substitution between vehicles. As the number of workers in the household increase, it should be the case the household needs more vehicles, and thus the sign on the worker count coefficient is expected to be positive.

In the fuel efficiency equation, as the number of miles driven increases, a household can decrease its fuel cost per mile by increasing its average fuel efficiency. Thus, the coefficient on the miles variable should be positive. As a household increases the number of vehicles it owns, it will be more likely to diversify the types of vehicles it chooses. As households diversify their vehicle stock, they will likely begin to own less fuel efficient vehicles, such as an SUV or van and thus the average fuel efficiency will likely decrease. Urban households are more likely to own cars, as opposed to SUVs and are thus likely to have a higher average fuel efficiency. As the number of household members increase, a household is likely to purchase larger vehicles to accommodate the increase in size. Thus, the coefficient on household size is expected to be negative.

In the miles equation, higher fuel efficiency is likely to encourage more driving as the fuel cost per mile is relatively low. If a household purchases an additional vehicle, it is likely to drive more miles. As a household's income increases, it is likely to have more money to spend and can drive more miles. Urban households are likely to have shorter commutes and access to more transportation options and are therefore likely to drive relatively fewer miles than rural households. The interaction term between the fuel cost per mile (proxy variable) and income allows for different responses based on income groups. We expect higher income households to be less responsive to price changes. Households with more children are likely to drive more miles as the number of activities will likely increase.

We explicitly calculate the weighted average fuel cost per mile by vehicle in the OLS model, which is a more accurate reflection of the variable we wish to calculate. However, because we allow households to adjust their average fuel efficiency in the SEM model, we cannot define the fuel cost per mile variable in the same way as before. We define the fuel cost per mile as follows in the OLS model,

$$P_M = \ln\left[\left(\frac{m_1}{M}\right)\frac{P_1}{MPG_1} + \left(\frac{m_2}{M}\right)\frac{P_2}{MPG_2}\right] \tag{5}$$

Where m_1 is the reported miles for vehicle 1, m_2 is the reported miles for vehicle 2 and $M = m_1 + m_2$. However, since we are trying to estimate households' average fuel efficiency, this presents a problem because we cannot extract the fuel efficiency values in the equation above.

In order to avoid this problem, we use the fact that our fuel price data is relatively uniformly distributed and is approximately $1.46. Furthermore, the average household fuel efficiency ($LNHHMPG$) is highly (negatively) correlated with the fuel cost per mile variable from the OLS model[17]. This is largely because the fuel price in our data is relatively uniform. Using these two facts, we have,

$$P_M^0 = \ln\left(\frac{1.46}{HHMPG}\right) \tag{6}$$

Since all households face the same fuel price in our sample, we exclude the fuel price from our estimation and instead use,

$$P_M^1 = LN\left(\frac{1}{HHMPG}\right) = LN(1) - LNHHMPG = 0 - LNHHMPG = -LNHHMPG \tag{7}$$

The sign of $LNHHMPG$ will only change the sign of the coefficient, but will not affect the magnitude or the overall explanatory power of our model. We therefore use $LNHHMPG$ as our fuel cost per mile proxy in the SEM model, which is also an endogenous variable and simplifies the incidence calculations.

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[17] The estimated correlation coefficient was approximately -0.95.

To incorporate the policy change, we replace $LNHHMPG$ with the following,

$$F_{VMT} = LN(1.46) - \ln\left(\frac{1.46 - 0.24}{HHMPG} + 0.012\right) \tag{8}$$

Since,

$$\begin{aligned} LNHHMPG &= LNHHMPG + LN(1.46) - LN(1.46) \\ &= -(-LNHHMPG - LN(1.46) + LN(1.46)) \\ &= -\left[LN\left(\frac{1.46}{HHMPG}\right) - LN(1.46)\right] \\ &= LN(1.46) - LN\left(\frac{1.46}{HHMPG}\right) \end{aligned} \tag{9}$$

We can then use the above equation to introduce the new fuel cost per mile value for each household.

4.3 Discrete-Continuous Choice Model

Small and Van Dender (2006) refer to the discrete-continuous choice model as the "theoretically preferred" model that best addresses the endogeneity between car choice and the demand for miles. These models are based on Dubin and McFadden's (1984) work on the estimation of energy demand through the discrete choice of appliances. Miles driven, like energy, is a derived demand in that miles in and of itself is not what people want to consume. Households demand vehicle miles (energy) based on their vehicle (appliance) choice. This method can be quite data-intensive in that as the number of vehicle choices increase, so do the possible combinations available to each household (West, 2002). Our Oregon sample is quite limited and makes this estimation method difficult to implement. Future studies may be able to incorporate more states with similar qualities to increase the sample size. Another problem we encounter with this method is the lack of temporal data. The discrete-continuous model can give us an idea of the future vehicle stock as a result of the policy change. Critics argue this policy will discourage fuel efficient vehicle purchases; this model may be able to better predict the long run effects of this policy on vehicle choice.

5. Data

The 2001 National Household Travel Survey (NHTS) is the main data source for this study. The survey is sponsored by the United States Department of Transportation and the Bureau of Transportation Statistics. The NHTS is the updated version of two previous surveys - the Nationwide Personal Transportation Survey (NPTS) and the American Travel Survey (ATS). While the NPTS focused on short, daily trips and the ATS focused on long trips, the NHTS asks respondents questions regarding both short and long distance trips and also includes all household members.

Within the NHTS data set, there are five files: household, vehicle, persons, daily trips and long trips. All of the variables used in the empirical estimation come from the household and vehicle files. Since this study focuses on the distributional impacts for Oregon households, we focused our attention on the 407 Oregon households involved in this survey. We have extracted the Oregon observations and any reference to the 2001 NHTS data set refers to the Oregon data. The NHTS contains data on household characteristics such as total household income, whether the household is in an urban or rural area, the number of children and the number of workers in the household. The vehicle file contains data on annual miles per vehicles, vehicle type, fuel efficiency and fuel prices for each vehicle. Since this study looks at households based on income and location, the following table describes the data by urban and rural indicators and by income groups. Definitions for urban and rural indicators and income groups follow.

Urban and rural indicators in the NHTS are based on Census classifications. According to the Census, urban is defined as having more than 1000 people per square mile in their city or town and more than 500 people per square mile in surrounding areas. All other areas are defined as rural. Thus, a household in an urban area takes the value of one and zero otherwise.

Table 3: Number of Oregon Households in Regressions by Location

Location	HH's in OLS	HH's in 3SLS	HH's Without Vehicles
Rural	101	68	29
Urban	238	180	3

Income is self-reported and households place themselves in one of eighteen groups. There are two variables in the survey that refer to household income - HHFAMINC and HHINCTTL. The former leaves blank those household members whose income was not stated. HHINCTTL randomly assigns those blanks a value within the range of those household members' whose income was recorded. We chose to use HHFAMINC to create the household income variable. Our income variable therefore likely understates the true household income value for some households[18]. Household income is approximated for this study by assigning each household the median value for the income category.

Table 4: Number of Oregon Households by Income[19]

Income Group	HH's in OLS	HH's in 3SLS	HH's Without Vehicles
1	39	27	13
2	74	47	10
3	61	50	4
4	60	45	2
5	39	25	2
6	66	54	0

[18] In the context of this research project, it would be more harmful to overstate household income than to understate the value.
[19] See A1 in the Appendix for income ranges in each group.

The highest income group is defined as a household with income greater than or equal to $100,000. The Oregon Census 2000 reports that only 1.8% of all Oregon households have an income greater than $200,000 (with no upper bound). Thus, we use $200,000 as an upper bound for the highest income group. These households were given a value of $150,000. Previous studies on VMT demand suggest using household expenditures in place of income as a measure of well-being however, expenditure data was not available (West, 2002 and Walls and Hansen, 1999). Since there were a lack of observations in a few of the eighteen groups, we classified households in one of six groups. The cutoff points for each income group were chosen to match the breakpoints assigned by the Census 2000. The proportion of households in each of the six groups were relatively consistent with the Census income groups. The table below compares the proportion of the sample in both the Census and the NHTS data set within different income ranges[20].

Table 5: Sample Representation as Compared to the Oregon Census 2000

Income Ranges ($)	% of Sample – Census	% of Sample - NHTS
<10,000	8.6	5.17
10,000~14,999	6.5	6.55
15,000~24,999	13.4	14.83
25,000~34,999	13.9	13.10
35,000~49,999	17.7	21.72
50,000~74,999	20.2	18.62
75,000~99,999	9.7	12.41
≥100,000	10	3.10

The 2001 NHTS provides an estimated gas price for each vehicle. However, these prices, which are based on the fuel type as indicated by the household and on gasoline

[20] Eight groups are listed here to give a better illustration of the actual distribution. From these categories, we divided our sample into six income groups.

price data collected by the Energy Information Administration (EIA) produce a relatively uniform distribution, ranging from approximately \$1.41 to \$1.47 per gallon, with the majority of households facing approximately \$1.46 per gallon (Energy Information Administration, 2003). Detailed gas prices are available from various sources, one of them being Oil Price Information Service (OPIS). It would be possible to get prices from different cities or counties within Oregon on a weekly, monthly or annual basis. Unfortunately, the NHTS does not have a location indicator and we cannot match gas prices to individual households. The gas price per gallon was divided by the fuel efficiency, to obtain the fuel cost per mile for each vehicle. The NHTS provides two fuel efficiency estimates - the EPA estimate and the EIA estimate. We chose to use the EIA estimate, which takes into account household and vehicle characteristics (Energy Information Administration, 2003). The EPA estimate on the other hand, tends to overstate fuel efficiency.

The fuel cost per mile for each vehicle was calculated as the price of gasoline divided by the vehicle's fuel efficiency. A household's fuel cost per mile was then calculated as the weighted average of all household vehicles, based on miles driven on each vehicle. To calculate the fuel cost per mile under the VMT fee, we subtract the state gasoline tax (24 cents per gallon for Oregon) from the gas price, divide the net gas cost by the fuel efficiency of each vehicle, add the per mile fee and again take the weighted average[21]. Unfortunately, our model cannot estimate how miles change for each vehicle within a household. Our sample provides a ‘snapshot’ of how households divide their total miles across their vehicles given one set of prices. We must therefore assume the ratio of total miles driven on each vehicle does not change given a change in the fuel cost per mile. Greene (1999) estimates an SEM with individual vehicles miles and fuel efficiency within a household, rather than total household miles and average fuel efficiency. This approach captures the substitutability between vehicles within a household. We capture this effect by

[21] See A2 in the the Appendix for more details.

calculating weighted averages for each household based on total miles driven on each vehicle. Fuel efficiency alone is not a choice variable at any one point in time in our model since it is predetermined once a vehicle is purchased (and vehicles are durable goods). Since we are using cross-sectional data from 2001, it would be inappropriate to use fuel efficiency for individual vehicles as a dependent variable. The weighted average on the other hand, based on miles driven, can be thought of as a choice variable. That is, a household can reallocate total miles driven between vehicles at any point in time, thus changing the value of the weighted average. Furthermore, Greene's method requires sub-samples, based on the number of vehicles in each household. In our case, when considering only Oregon households, there is an insufficient number of households in the sub-samples, and it would be difficult to implement Greene's method.

Self-reported annual miles for each vehicle were used for this study. Household miles are therefore the sum of all individual vehicle miles. The NHTS reports annual miles based on three different methods. Respondents were asked to record their odometer readings at two points in time, most often between two and three months apart. In many cases only one odometer reading was reported and in some cases there were no recordings. In the second method, mileage was recorded for the day of the survey. This measure will depend on the day of the week (driving to work or for recreation, for example) and will not accurately measure total mileage for one year. The third measure, self-reported annual miles may be subject to certain biases but we assume the average household reports their mileage accurately[22].

The summary statistics for the most part are consistent with previous studies. The average household in urban areas had a higher fuel efficiency than its rural

[22] The NHTS also includes a BESTMILE variable, which takes the best approximation to annual miles, meaning that the value for this variable could have come from any one of these three methods. We viewed this as an inconsistent way to record annual miles in that the origin of the variable will be different from household to household.

counterpart[23]. Rural households tend to drive more miles annually than urban households, which may be in part due to longer commutes to work. There is a higher proportion of automobiles and station wagons in urban areas than there are in rural areas and a higher proportion of pickup trucks in rural areas than in urban areas. The average urban household has a household income of approximately $52,394.50 compared to an average rural household income of approximately $48,266.85 when all households are considered. Income is self-reported in this survey, which may lead to biased estimates, however, it will be difficult to determine the overall impact of that bias.

Table 6: Breakdown of Vehicle Type by Location

Type of Vehicle	Urban (%)	Rural (%)
Car or Station Wagon	50	38
Truck	21	36
SUV	13	13
Van	8	5
Motorcycle	5	3
RV	2	2
Other	1	3

Crandall and Weber (2005) argue that the Census definition of urban and rural may not be ideal because it fails to incorporate the fact that areas around urban or metropolitan cities, which are 'rural' according to the Census, still have full access to urban transportation systems and other services that truly isolated areas may not have access to. Instead the authors propose an alternative definition that incorporates location relative to large cities and whether or not there are linkages to those cities. Such a classification system would more accurately model a household's access to

[23] Approximately 21.1128 MPG in urban areas compared with approximately 19.665 MPG in rural areas.

transportation and employment opportunities. Unfortunately, the NHTS does not provide the households' city or county location and we could not incorporate such definitions. The NHTS does include data on population density at the block and tract level, however, households are assigned to one of eight categories and this variable was therefore not viewed as an accurate measure.

Households in our survey on average hold on to their vehicles for twelve years in rural areas and eleven years in urban areas, a few more years than other estimates (Barnes and Langworthy, 2003).

We started with 407 Oregon households with a total of 893 vehicles. From this sample, we assigned weighted averages based on vehicle miles for fuel efficiency and fuel cost per mile. If a household was missing fuel efficiency for one or multiple vehicles, that vehicle was assigned the average of the household's remaining vehicles' fuel efficiency. If fuel price was missing, because there was a relatively uniform distribution of prices, the missing value was assigned the sample average.

If annual miles were not reported, or was reported as missing in our sample, it was assumed that the vehicle was not used in that year and these vehicles were ignored. Thus, these vehicles were also excluded in the household vehicle count. For example, if a household reportedly owned four vehicles, but reported zero miles for one vehicle, we readjusted vehicle count to be three. Furthermore, recreational vehicles were also ignored and households' vehicle count was again adjusted accordingly.

After these adjustments, if a household was missing any of the variables included in the regression, the household was excluded. Thus, our OLS regression includes 339 households and our 3SLS model includes 248 households.

6. Estimation and Results

Two separate regressions were run. First, we estimate a simple Ordinary Least Squares (OLS) regression of annual household miles. Second, we take the OLS model a step further and account for the endogeneity between the number of cars a household chooses to own, car type (fuel efficiency) and the number of miles a household drives annually. To capture this, we estimate a SEM using a Three-Stage-Least Squares (3SLS) regression.

6.1 Ordinary Least Squares Model Results

Table 7: Dependent Variable – Annual Household Miles (Logarithmic) [24]

Variable Name	Coefficient	Stand.Error	T-Statistic
Constant	-17.5668	6.2495	-2.81
P_M	-8.6814	2.3927	-3.63
I	2.1978	0.6144	3.58
$P_M * I$	0.71	0.2356	3.01
$P_M * SUB$	0.4548	0.4012	1.13
U	-0.1759	0.0952	-1.85
C	0.5349	0.1293	4.14
SUB	1.4074	1.0521	1.34
MALE	0.1678	0.0876	1.92
WORK	0.2218	0.053	4.19
CHILD	0.0378	0.0394	0.96

All signs were as expected, based on economic theory and the findings in previous studies[26]. Income and miles driven are positively correlated and significant, as are the

[24] Italicized variables are logarithmic.
[26] All interpretations are based on a 10% significance level.

number of vehicles owned by a household. The dummy variable for urban households was significant and suggests urban households drive fewer miles than rural households. Households with male respondents drive more miles than households with female respondents. Household annual miles increase as the number of workers increase, as expected. As the fuel cost per mile increases, households will reduce the overall number of miles driven, however, the overall reduction will depend on household income and whether or not the household is able to substitute between vehicle types. The fuel cost per mile and the interaction term between the fuel cost per mile and income were statistically significant. However, the interaction term between the fuel cost per mile and the substitution variable was not found to be significant.

As the number of children increases, we would expect the household to drive more miles as suggested by our model, however, this is not statistically significant. Though the substitution variable was not statistically significant, it has the expected sign, as discussed in Section 4. That is, if a household is able to substitute between vehicles, we would expect them to drive more miles relative to a household (all else equal) that is unable to substitute between vehicles.

We can interpret the coefficients of the logarithmic terms as elasticities. Our model assumes that the elasticity of annual household miles driven with respect to fuel cost per mile varies across income groups. As expected, higher income groups, on average, are less responsive to changes in the fuel cost per mile. The coefficient of the interaction term between the fuel cost per mile and the substitution dummy variable also allows for the elasticity to vary between households that are able to substitute between vehicle types, and those that cannot. Though not statistically significant, this coefficient was as expected and tells us that households that are not able to substitute between vehicle types have a more elastic demand, as expected[27]. These households

[27] The elasticity of miles driven with respect to the fuel cost per mile can be calculated as: $\varepsilon_{M,P_M} = -8.6814 + 0.71 * I + 0.4548 * SUB$.

are more sensitive to changes in the fuel cost per mile. It should be noted that the elasticities will vary by households, however, we use the average income value for each group to give us an approximation.

Table 8: Elasticity by Income Group – Based on Average Income

Income Group	Average Income	Elasticity w/ SUB	Elasticity w/o SUB
1	$9,055.90	1.7577	2.2125
2	$21,983.11	1.128	1.5828
3	$36,899.07	0.7603	1.2151
4	$51,952.61	0.5174	0.9722
5	$67,394.80	0.3326	0.7874
6	$106,043.36	0.0108	0.4656

While the elasticities tell us how different income groups respond to the policy change we can use the Suits Index (Suits, 1977) as a way to measure the overall regressivity of a tax, or to compare the changes in regressivity as a result of a structural or policy change[28]. In our case, we can compare the regressivity of the gas tax to the VMT fee. The Suits Index, bounded between -1 and 1, is convenient in that it provides one number that can be compared across tax regimes. A value of -1 implies the lowest income group bares the entire burden of the tax; a value of 1 implies the highest income group bares the entire tax burden. A value of 0 implies the proportion of the overall tax paid by each income group is exactly equal to the proportion of the population represented by that income group. Under the gasoline tax, the Suits Index is approximately -0.133 compared to a Suits Index approximately equal to -0.142 under the VMT fee, implying the VMT fee will shift some of the tax burden from the higher income groups to the lower income groups, making it slightly more regressive[29].

[28] See A4 in the Appendix for more details.
[29] See A4 in the Appendix for the computation of the Suits Index.

We also calculate the welfare impacts and changes in consumer surplus, assuming a linear demand function. We use the change in fuel expenditures as a measure of well-being.

Table 9: Average Changes in Consumer Surplus, Tax Revenue and Welfare by Income ($/Household) – OLS Model

Income Group	Average Change in Consumer Surplus	Average Change in Tax Revenue	Average Change in Welfare
1	-7.36	-4.97	-12.33
2	-6.40	-5.30	-11.70
3	9.44	4.37	13.81
4	-2.34	-6.37	-8.71
5	28.69	10.12	38.81
6	12.74	2.68	15.42

Table 10: Average Changes in Consumer Surplus, Tax Revenue and Welfare By Location ($/Household) – OLS Model

Location Group	Average Change in Consumer Surplus	Average Change in Tax Revenue	Average Change in Welfare
Urban	-0.56	-3.86	-4.42
Rural	17.50	7.80	25.30

Unlike the static model case, we are able to calculate consumer surplus because we allow miles to vary[30]. In the static model, since miles do not vary, only total revenue collected will change as the price per mile changes. The OLS model allows households to adjust miles driven as the price per mile changes. Thus, the static model tells us that as the fuel cost per mile increases, total revenue collected by the state agency increases. However, in the OLS model, the same price increase may not

[30] See A3 in the Appendix for the computation of consumer surplus and tax revenue.

necessarily imply an increase in total revenue. Here it depends on various attributes such as income and household location. These factors, along with the other factors in our estimation, will determine how households respond to changes in their fuel cost per mile. Total welfare in this case is calculated as the change in consumer surplus plus the change in tax revenue. Generally, welfare is defined as the total consumer and producer surplus added as a result of a change – in this case, a change in price. To society as a whole, it does not matter whether consumers or producers gain more. Thus, a positive welfare gain may reflect an overall gain for consumers or producers. Since we do not estimate a cost, or supply, function, we use revenue collected by the government as a 'cost' function.

6.2. Three-Stage-Least-Squares Model Results

Table 11: 3SLS Estimation Results (Logarithmic) [31]

Count Equation (C)	Coefficient	Stand.Error	Z-STAT
I	0.133	0.023	5.84
LNHHMPG	-0.316	0.081	-3.91
U	-0.081	0.059	-1.37
WORK	0.115	0.026	4.44
MPG Equation (*LNHHMPG*)	Coefficient	Stand.Error	Z-STAT
M	0.457	0.037	12.48
C	-1.10	0.217	-5.04
I	-0.069	0.033	-2.06
U	0.065	0.069	0.94
HHSIZE	-0.024	0.078	-0.31
Miles Equation (M)	Coefficient	Stand.Error	Z-STAT
LNHHMPG	2.317	0.218	10.64
C	2.628	0.304	8.64
I	0.160	0.040	4.00
U	-0.116	0.135	-0.86
LNHHMPG I*	-0.018	0.014	-1.35
CHILD	0.011	0.033	0.34

Where, variables that were not modified from the OLS model are as defined in the previous section. Not included in the OLS model is the number of persons in a given household (HHSIZE) and *LNHHMPG*, which is the household's weighted average fuel efficiency, and serves as the fuel cost per mile proxy in the miles equation. The

[31] Italicized variables are logarithmic.

LNHHMPG that appears in the count and MPG equations should be interpreted as the household fuel efficiency and not the fuel cost per mile.

Based on these results, we solve for the three endogenous variables – vehicle count, household fuel efficiency and household annual miles – in terms of the exogenous variables[32].

Under the gasoline tax, we use the following equations,

$$C=\left(\frac{0.002CHILD}{0.027-0.008I}\right)+0.133I+\left(\frac{0.006I}{0.027-0.008I}\right)-\left(\frac{0.008HHSIZE}{0.027-0.008I}\right)-0.081U$$
$$+\left(\frac{0.001U}{0.027-0.008I}\right)+0.115WORK+\left(\frac{0.004WORK}{0.027-0.008I}\right) \quad (10)$$

$$LNHHMPG=\frac{-0.017I+0.024HHSIZE-0.004U-0.005CHILD-0.012WORK}{0.027-0.008I} \quad (11)$$

$$M=\left(\frac{-0.007CHILD}{0.027-0.008I}\right)+0.471I-\left(\frac{0.025I}{0.027-0.008I}\right)+0.053HHSIZE+$$
$$\left(\frac{0.034HHSIZE}{0.027-0.008I}\right)-0.337U-\left(\frac{0.005U}{0.027-0.008I}\right)+0.277WORK \quad (12)$$
$$-\left(\frac{0.017WORK}{0.027-0.008I}\right)$$

[32] The coefficient values used here are rounded. A more accurate version was used in the actual estimation process, however, due to formatting issues, these values were not written in this paper.

In order to incorporate the policy change, we replace the fuel cost per mile variable (*LNHHMPG*) in the miles equations with a new variable defined as the fuel cost per mile under the VMT fee,

$$F_{VMT} = \ln(1.46) - \ln\left(\frac{1.46 - 0.24}{HHMPG} + 0.012\right) \tag{13}$$

Our new fuel cost per mile, F_{VMT} is still a function of the household fuel efficiency, $LNHHMPG$. Because of this newly defined variable, we cannot solve explicitly for $LNHHMPG$ as a function of the exogenous variables. We therefore apply Newton's Method[33]. We first define a new function, f(HHMPG), set the function equal to zero, then solve for $\overline{LNHHMPG}$ iteratively. Once we have convergence, $\overline{LNHHMPG}$ is then used to solve for vehicle count and miles as a function of the exogenous variables.

We base our incidence analysis under the VMT fee on the following set of equations,

$$C = 0.133I - 0.316\overline{LNHHMPG} - 0.081U + 0.115WORK \tag{14}$$

$$\begin{aligned} M = {} & 2.32F_{VMT} + 0.51I - 0.83\overline{LNHHMPG} - 0.33U + 0.30WORK - 0.02F_{VMT} * I \\ & +0.01CHILD \end{aligned} \tag{15}$$

$$\begin{aligned} 0 = f(HHMPG) = {} & 0.40 - 1.06F_{VMT} + 0.01I - 1.03\overline{LNHHMPG} + 0.003U \\ & +0.01WORK + 0.01F_{VMT} * I + 0.01CHILD - 0.02HHSIZE \end{aligned} \tag{16}$$

Based on these equations, we calculate the impacts of the same policy change as in the OLS model.

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[33] See A5 in the Appendix for details.

Table 12: Average Changes in Consumer Surplus, Tax Revenue and Welfare by Income ($/Household) – 3SLS Model

Income Group	Average Change in Consumer Surplus	Average Change in Revenue	Average Change in Welfare
1	-$114.52	-$1.82	-$116.33
2	-$140.63	-$1.56	-$142.19
3	-$126.44	-$0.74	-$127.18
4	-$117.31	-$0.80	-$118.11
5	-$100.86	-$0.17	-$101.03
6	-$57.82	0.11	-$57.70

Table 13: Average Changes in Consumer Surplus, Tax Revenue and Welfare by Location ($/Household) – 3SLS Model

Location Group	Average Change in Consumer Surplus	Average Change in Revenue	Average Change in Welfare
Urban	-$80.15	-$1.70	-$81.85
Rural	-$119.88	-$0.44	-$120.32

On average, all households regardless of income and location, will drive fewer miles and lose consumer surplus. Relative to the OLS model results, the state agency, on average, will collect less revenue as households adjust their vehicle stock and miles driven. The 3SLS model predicts an overall reduction in welfare.

The Suits Index for the 3SLS model was approximately -0.153 under the gasoline tax and -0.151 under the VMT fee. Contrary to the OLS model, this suggests the VMT fee is slightly more progressive than the gasoline tax; some of the tax burden will be shifted from lower to higher income households.

Our 3SLS model predicts households will own, on average, 0.04 more vehicles, drive 2,374 less miles annually and decrease their average fuel efficiency by approximately

2.68 MPG. These findings are consistent with our theory – if households realize the true cost of driving and pay accordingly, we expect them to drive fewer miles, taking only trips that are of the highest value to them. Furthermore, the relative price of driving will decrease, ceteris paribus, for fuel inefficient vehicles, which may encourage households to use less fuel efficient vehicles.

7. Conclusion and Future Research

This paper predicts the economic impacts of a switch from the current gasoline tax to a vehicle mile tax. When we consider income groups, the static and OLS models produce similar results; the VMT fee is more regressive than the current gasoline tax. The static model assumes all variables are fixed, while the OLS model allows households to adjust annual miles. When we adjust households' fuel cost per mile, both models predict some of the burden will shift from higher to lower income households.

The SEM model predicts the average household in all groups will lose consumer surplus. According to this model, all households will reduce their annual fuel expenditures. The state agency will collect less revenue from all income groups, except – on average – from households in the highest income group as a result of the new policy.

The overall impact of a switch from the gasoline tax to a vehicle mile tax depends largely on assumptions made about household behavior. In particular, it depends on how our demand model is defined. The magnitude of the impact varies by model specifications. The OLS and 3SLS model results are consistent with previous findings; the gasoline tax and the VMT fee are both regressive, the VMT fee being slightly more regressive than the gasoline tax based on the OLS results, and slightly more progressive according to the 3SLS model. Findings from the 3SLS model appears to be consistent with concerns about fuel efficiency; the average household is expected to reduce their average fuel efficiency by approximately 2.68 MPG. The average household is, however, expected to reduce annual miles driven by approximately 2,374 miles. This may offset some of the environmental impacts and improve road safety. These findings are consistent with our theory – if agents realize their true costs and are forced to pay their share of road wear costs, we expect them to reduce total miles driven, taking only the trips they value most (Small, et al, 1989). Our models assume an immediate and complete switch from the gasoline tax to a vehicle mile tax, when in reality, the switch will be gradually phased in over a period of at least twenty years.

While the OLS model allows households to adjust their miles given a change in price, it does not predict vehicle ownership. The substitution variable (SUB) allows us to capture the substitutability between vehicle types. To fully predict the impact of a policy change, we must also estimate vehicle ownership. The 3SLS model does this in a continuous setting and allows households to adjust the number of vehicles, their average fuel efficiency and miles driven. This model – in theory – is more realistic than the OLS model. Small and Van Dender (2006) refer to the discrete-continuous choice model specification as the "theoretically preferred" model, which is based on Dubin and McFadden's (1984) work. However this method requires more data that could not be supported by the 2001 NHTS Oregon sample used in this paper. Future studies can incorporate more data and estimate a discrete-continuous choice model.

The 3SLS model presented here addresses the substitutability between vehicles to a certain degree by incorporating average household fuel efficiency as a dependent variable. It is possible to estimate (explicitly) the substitutability between individual vehicle miles, rather than estimating household miles. However, such estimation is out of the scope of this paper and is left for future research.

When this paper was submitted, the results of the SEM were considered quite preliminary. The interaction term between the fuel cost per mile and income in the miles equation appears to have caused some problems in the estimation process. The magnitude of the predicted changes as a result of the policy is quite large, particularly for the lower income groups and should be explored further. The model presented in this paper is our first attempt to address the endogeneity between the dependent variables. Time and data limitations made it impossible to test other specifications thoroughly. We leave this for future research.

Our data is limited to Oregon households in 2001. Including other states that are similar to Oregon may improve the estimated results by increasing variation and the sample size. More recent data is likely to include hybrid vehicles and provide a better sense of the overall impact of a policy switch on the current vehicle stock. Increasing the sample size may also allow us to estimate a discrete-continuous choice model.

References

Barnes, Gary and Peter Langworthy. “The Per-Mile Costs of Operating Automobiles and Trucks" Minnesota Department of Transportation, June 2003.

Bento, Antonio, et al. “Distributional and Efficiency Impacts of Gasoline Taxes: An Econometrically-Based Multi-Market Study" January 2005.

Button, Kenneth. “The Rationale for Road Pricing" *Road Pricing: Theory and Evidence”*, 2004, 9: 3-25.

Chernick, Howard and Andrew Reschovsky. “Who Pays the Gasoline Tax?" *National Tax Journal*, 1997, 50(2): 233-259.

Chouinard, Hayley and Jeffery M. Perloff. “Incidence of Federal & State Gasoline Taxes" Working Paper, 2003.

Crandall, Mindy and Bruce Weber. “Defining Rural Oregon: An Exploration" *Rural Studies Program*, November 2005.

Dubin, Jeffery A. and Daniel L. McFadden. “An Econometric Analysis of Residential Electric Appliance Holdings and Consumption" *Econometrica*, 1984, 52(2).

Energy Information Administration. “Supplemental Energy-Related Data for the 2001 National Household Travel Survey" Appendix K: Documentation on Estimation Methodologies for Fuel Economy and Fuel Cost, U.S. Department of Transportation, June 2003.

Greene, David L., James R. Kahn and Robert C. Gibson. “Fuel Economy Rebound Effect for U.S. Household Vehicles" *The Energy Journal*, 1999.

Gujarati, Damodar N. Essentials of Econometrics. Boston, Massachusetts: McGraw-Hill, 2006.

Kulash, Damian J. “Transportation User Fees in the United States" *Transportation Quarterly*, Summer 2001, 55(3): 22-49.

National Household Travel Survey. “2001 National Household Travel Survey: User's Guide" June 2004.

Oregon Department of Transportation. “Oregon Transportation Plan: Public Hearing Draft, Vol. 1" June 29, 2006.

Parry, Ian W.H. and Kenneth Small. “Does Britain or the United States Have the Right Gasoline Tax?" *The American Economic Review*, September 2005, 95(4): 1276-1289.

Poterba, James M. “Is the Gasoline Tax Regressive?" Working Paper, National Bureau of Economic Research, 1990.

Small, Kenneth and Kurt Van Dender. “Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect" Working Paper, 2006.

Small, Kenneth, Clifford Winston and Carol A. Evans. Road Work: A New Highway Pricing & Investment Policy. Washington, D.C.: The Brookings Institution, 1989.

Suits, Daniel B. “Measurement of Tax Progressivity" *American Economic Review*, 1977, 67(4): 747-752.

U.S. Department of Transportation, Bureau of Transportation Statistics. “NHTS 2001 Highlights Report" Washington, DC, 2003.

U.S. Department of Energy. “Many Factors Affect MPG" Accessed on June 4, 2007. Available at: http://fueleconomy.gov/feg/factors.shtml.

Walls, Margaret and Jean Hanson. “Distributional Aspects of an Environmental Tax Shift: The Case of Motor Vehicle Emissions Taxes" *National Tax Journal*, 1999.

West, Sarah. “Distributional Effects of Alternative Vehicle Pollution Control Policies" Extended Working Paper to Accompany the Shorter Version Forthcoming in *Journal of Public Economics*, 2002.

Whitty, James, Jack Svadlenak and Darel Capps. “Public Involvement and Road User Charge Development: Oregon's Experience" Oregon Department of Transportation, March 2006.

APPENDIX

Appendix

A1. Income Groups

The NHTS assigns households into one of 18 categories. We assigned the median value of each category to each household.

Income Category	Income Ranges	Value Assigned to Household
1	\$0 ~ \$5,000	\$2,500.00
2	\$5,000 ~ \$9,999	\$7,499.50
3	\$10,000 ~ \$14,999	\$12,499.50
4	\$15,000 ~ \$19,999	\$17,499.50
5	\$20,000 ~ \$24,999	\$22,499.50
6	\$25,000 ~ \$29,999	\$27,499.50
7	\$30,000 ~ \$34,999	\$32,499.50
8	\$35,000 ~ \$39,999	\$37,499.50
9	\$40,000 ~ \$44,999	\$42,499.50
10	\$45,000 ~ \$49,999	\$47,499.50
11	\$50,000 ~ \$54,999	\$52,499.50
12	\$55,000 ~ \$59,999	\$57,499.50
13	\$60,000 ~ \$64,999	\$62,499.50
14	\$65,000 ~ \$69,999	\$67,499.50
15	\$70,000 ~ \$74,999	\$72,499.50
16	\$75,000 ~ \$79,999	\$77,499.50
17	\$80,000 ~ \$99,999	\$89,999.50
18	\$100,000 or greater	\$150,000.00[34]

[34] The 2001 NHTS does not have an upper bound for this last income group. According to the Census 2000 for Oregon, only 1.8% of all households have a total income greater than \$200,000.

A2. Variable Description OLS and 3SLS Models

The data used in the OLS and 3SLS estimations are based on the NHTS data, or were derived from the NHTS data set. All variables used are described below. If the variable was modified, it is described in this table.

Variable	Variable Name	Description
P_M	Fuel Cost Per Mile Under the Gasoline Tax	Weighted average by miles driven. The fuel cost per mile used in the estimation is the fuel cost per mile under the gasoline tax. Fuel cost per mile for vehicle *i* is defined as: $\frac{P_i}{MPG_i}$ Where P_i is the reported fuel price and MPG_i is the EIA adjusted fuel efficiency in the NHTS data. If the MPG was not reported for a particular vehicle, the average for reported vehicle MPG was used for the missing value(s). Thus, for a household with two vehicles, $P_M = \ln\left[\left(\frac{m_1}{M}\right)\frac{P_1}{MPG_1} + \left(\frac{m_2}{M}\right)\frac{P_2}{MPG_2}\right]$ Where m_1 is the reported miles for vehicle 1, m_2 is the reported miles for vehicle 2 and $M = m_1 + m_2$.
I	Household Income	NHTS reported income group. Households put themselves in one of 18 income categories based on income ranges. We then assigned households the median value for their category. For example, income group 3 was defined as a household that

		earns between \$10,000 and \$14,999. Thus, for this household, $I = \ln(12{,}499.50)$.
SUB	Substitution Indicator	Dummy variable equal to 1 if the household owns more than one type of vehicle and 0 otherwise. This is based on the NHTS variable for "vehicle type." 1 = Car/Station Wagon 2 = Van 3 = SUV 4 = Pickup Truck 5 = Other Truck 6 = RV 7 = Motorcycle 91 = Other We treat values 4 and 5 as the same, and consider these as "trucks," though this was not an issue in the Oregon OLS sample. For example, if a household owns two cars, SUB=0. If a household owns a car and a van, SUB=1.
U	Location Indicator	Dummy variable equal to 1 if the household is located in an urban area, 0 otherwise. Location indicators are based on the Census 2000 definition. According to the Census 2000, an urban area is defined as an area with: 1. "Core census block groups or blocks that have a population density of at least 1,000 people per square mile and 2. "Surrounding census blocks that have an

		overall density of at least 500 people per square mile." (From U.S. Census Bureau, Available at: http://www.census.gov/geo/www/ua/ua_2k.html. Accessed on August 24, 2007)
C	Vehicle Count	This variable was modified from the vehicle count variable in the NHTS dataset. If a household reported zero miles driven on a vehicle, that vehicle was excluded, and subtracted from the NHTS vehicle count variable. Also, if miles for a vehicle was missing, it was again assumed the vehicle was not used and was subtracted from the NHTS vehicle count.
MALE	Gender of Household Respondent Indicator	Dummy variable equal to 1 if the household respondent is a male, 0 otherwise. Unmodified from the NHTS data set, except that the NHTS uses values 1 and 2, which we changed to 0 or 1. NHTS: Defines Male=1, Female=2. We change the NHTS variable to Male=1, Female=0.
WORK	Number of Workers in Household	Unmodified variable from the NHTS dataset.
CHILD	Number of Children in Household	Derived from the NHTS dataset. We define the number of children as the total number of people in the household minus the number of adults.
$P_M * I$	Product of Fuel Cost Per Mile and Income	This is an interaction term between the fuel cost per mile for the household and the household income. This allows for different elasticities for different income groups.

$P_M * SUB$	Product of Fuel Cost Per Mile and the Substitution Indicator	This is an interaction term between the fuel cost per mile for the household and the substitution dummy variable. This allows for different elasticities for households with multiple vehicle types and those without.
LNHHMPG	Household (Weighted) Average Fuel Efficiency	This variable appears in the SEM model and is used as a dependent variable as well as a proxy for the household fuel cost per mile. For a household with two vehicles, this variable is calculated as: $LNHHMPG = \ln\left[\left(\frac{m_1}{M}\right)MPG_1 + \left(\frac{m_2}{M}\right)MPG_2\right]$ Where m_1 is the reported miles for vehicle 1, m_2 is the reported miles for vehicle 2 and $M = m_1 + m_2$. MPG_1 is the EIA adjusted fuel efficiency for vehicle 1 and MPG_2 is the EIA adjusted fuel efficiency for vehicle 2.

A3. Consumer Surplus, Revenue and Welfare Definitions

To calculate the change in consumer surplus for the individual household, we use the following equation,

$$SURPLUS = \frac{1}{2}\left\{(P_M - P_{VMT}) * (MILES_{GAS} + MILES_{VMT})\right\}$$

The difference $(P_M - P_{VMT})$ determines the sign of the change. If the fuel cost per mile under the VMT (P_{VMT}) fee exceeds the fuel cost per mile under the gasoline tax (P_M), we expect a reduction in total consumer surplus as we move upward along the linear demand curve. Similarly, if the fuel cost per mile decreases under the new policy, we expect household miles to increase as it becomes cheaper for households to drive and thus, increase the total consumer surplus as we move downward along the linear demand curve.

Revenue collected by the state agency for each household is calculated using the following equation,

$$REVENUE = 0.012 * MILES_{VMT} - \left[\left(\frac{0.24}{HHMPG}\right) * MILES_{GAS}\right]$$

Household miles are based on the predicted (fitted) values estimated by the model, first under the gasoline tax ($MILES_{GAS}$), then under the VMT fee ($MILES_{VMT}$). To calculate the net gasoline taxes collected, we consider only the \$0.24 collected per gallon sold. Since we do not estimate the miles driven on individual vehicles, we cannot calculate the gasoline tax revenue collected by vehicle. Instead, we use the weighted average household fuel efficiency ($HHMPG$) to calculate the per-mile cost in terms of the gasoline tax. We consider only a flat-rate VMT fee, and we can calculate the revenue collected by multiplying the per-mile fee ($0.012) by the predicted household miles under the VMT fee.

Since we do not calculate a supply function, we use the revenue collected by the state agency to calculate the welfare changes, rather than the standard producer's surplus. Thus, welfare for each household is calculated as,

$$WELFARE = SURPLUS + REVENUE$$

A4. Suits Index (Suits, 1977)

The Suits Index is another way to measure the regressivity of a tax, or to compare the changes in regressivity as a result of a structural change. In our case, we can compare the regressivity of the gas tax to the VMT fee. The Suits Index is convenient in that it provides one number that can be compared across tax regimes.

Similar to the Gini Coefficient, the 45 degree line represents the points were the proportion of the tax paid by each income group exactly equals the proportion of the population. Points above the 45 degree line suggest lower income groups pay more than their proportion of total income, suggesting a regressive tax. Similarly, points below the 45 degree line would suggest lower income families pay a lower proportion of a tax than their proportion of income, suggesting a progressive tax. West (2002) and Walls and Hanson (1999) both conclude a per-mile emissions fee is regressive, by calculating a Suits Index.

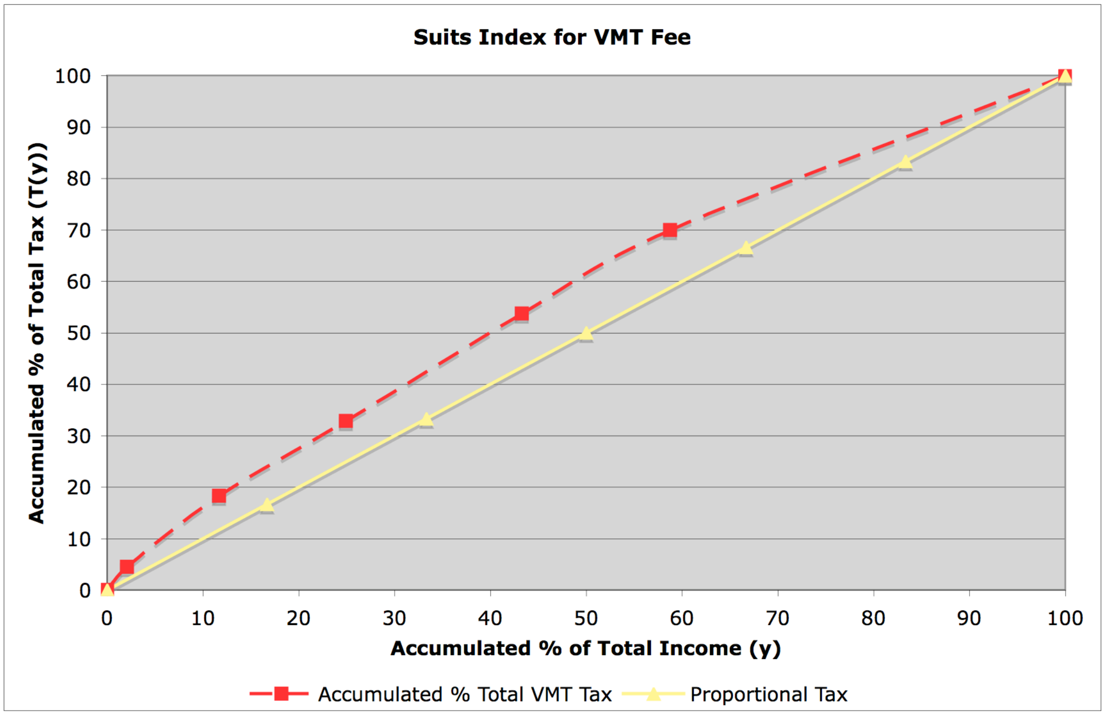
The Suits Index is computed as:

$$S = 1 - \frac{1}{5000}\int_{0}^{100} T(Y)dy$$

We multiply the area by $\frac{1}{5000}$ to keep the Suits Index bounded by -1 and 1, since the area of the upper or lower triangle will be 5000. A value of -1 suggests a perfectly regressive tax where the lowest income group bares the entire tax burden. On the other extreme, a value of 1 suggests the highest income group bares the entire tax burden. A Suits Index equal to 0 implies we are on the 45 degree line and the tax is exactly proportional. Thus, we are attempting to calculate the area between the curve and the 45 degree line. Since we only have 6 income groups, and thus 6 discrete points, we can approimate the integral as:

$$\int_{0}^{100} T(Y)dy \approx \frac{1}{2}\sum_{i=0}^{6}\{[T(y_i) + T(y_{i-1})](y_i - y_{i-1})\}$$

Figure 1: Suits Index Under the VMT Fee Based on OLS Model Results



Where y_i refers to the accumulated income on the x-axis, $T(y_i)$ refers to the accumulated percent of total taxes paid on the y-axis and $y_i = T(y_i) = 0$ when i = 0. Using the Suits Index on our data, we have the following points:

Table A4.1: Values Used to Calculate the Suits Index Based on the OLS Model

Income Group	Accumulated Income (%)	Accumulated Gas Tax (%)	Accumulated VMT Fee (%)
1	2.0808	4.20573	4.49831
2	11.6649	17.46371	18.33979
3	24.92588	32.396867	32.82791
4	43.29078	52.763577	53.74785
5	58.7658	69.654037	69.99069
6	100	100	100

Table A4.2: Values Used to Calculate the Suits Index Based on the 3SLS Model

Income Group	Accumulated Income (%)	Accumulated Gas Tax(%)	Accumulated VMT Fee (%)
1	2.113	4.325	4.231
2	10.069	16.338	16.135
3	24.127	33.718	33.508
4	41.869	53.879	53.676
5	54.624	66.703	66.546
6	100	100	100

A5. Applying Newton's Method to Find LNHHMPG

To solve this system of equations, we want to write each endogenous variable in terms of only the exogenous variables. Estimating changes in miles, fuel efficiency or vehicle count without doing so does not incorporate the simultaneity between equations.

Under the gasoline tax, this is straight forward. We can easily write each endogenous variable as a function of the five exogenous variables. However, since we incorporate a new fuel cost per mile variable under the VMT fee, we find that we cannot solve explicitly for the household fuel efficiency. We can use Newton's Method to find the fitted value, $\overline{LNHHMPG}$ such that $f(HHMPG) = 0$. Finding such a vector allows us to use these fitted values for each household to solve, explicitly, for count and miles as a function of the exogenous variables.

$$0 = f(HHMPG) = 0.40 - 1.06F_{VMT} + 0.01I - 1.03\overline{LNHHMPG} + 0.003U + 0.01WORK$$
$$+0.01F_{VMT} * I + 0.01CHILD - 0.02HHSIZE$$

Our endogenous variable is $LNHHMPG$, however, for simplicity we can solve for HHMPG and use these values to find $LNHHMPG$. We start by 'guessing' an initial value, call this $HHMPG_0$. In this case, we use $HHMPG_0 = 20$, which is a vector that assigns each household an average fuel efficiency of 20 MPG. Then, by Newton's Method,

$$HHMPG_{N+1} = HHMPG_N - \left[\frac{f(HHMPG_N)}{\left(\frac{\partial f(HHMPG)}{\partial HHMPG} \right) \Big|_{HHMPG_N}} \right]$$

Convergence occurs when $HHMPG_N = HHMPG_{N+1}$. After five iterations, $HHMPG_4 = HHMPG_5$, and we use the natural log of these predicted values to then calculate household vehicle count and household miles driven.

A6. Average Fuel Expenditure by Income and Location for Each Model

Care should be taken when interpreting these results. Using the reported values alone or as a percentage of income may be slightly misleading because these values are based on household annual miles, which for the later two models, are predicted by the models. The static model on the other hand is based on the reported miles. In all three cases, income does not vary in the sense that these values are based on household reported values from the NHTS data.

Income Group	Static Model: Average Expenditures		OLS Model: Average Expenditures		3SLS Model: Average Expenditures	
	Gas	VMT	Gas	VMT	Gas	VMT
1	$658.90	$666.72	$426.20	$418.10	$444.55	$408.51
2	$917.84	$923.03	$707.21	$703.75	$710.14	$665.31
3	$1174.01	$1169.61	$982.23	$980.39	$965.73	$926.10
4	$1595.10	$1595.33	$1357.34	$1355.65	$1244.73	$1205.79
5	$1858.85	$1833.51	$1795.07	$1776.10	$1425.17	$1393.54
6	$1992.60	$1986.60	$1856.69	$1843.96	$1713.14	$1696.05
Location	Gas	VMT	Gas	VMT	Gas	VMT
Rural	$1600.17	$1586.56	$1460.16	$1446.18	$1387.87	$1357.38
Urban	$1249.55	$1251.58	$1073.05	$1069.04	$1013.55	$977.54

A7. Average Household Income and Number of Households for Each Model

Income Group	Static Model: Number of Households		OLS Model: Number of Households		3SLS Model: Number of Households	
	# HHs	Avg.Income	#HHs	Avg.Income	#HHs	Avg.Income
1	39	$9935.40	39	$9,055.90	27	$10,356.64
2	75	$22,432.83	74	$21,983.11	47	$22,395.32
3	65	$37,037.96	61	$36,899.07	50	$37,199.48
4	62	$52,096.27	60	$51,952.61	45	$52,166.03
5	40	$67,499.50	39	$67,394.80	25	$67,499.47
6	67	$109,962.37	66	$106,043.36	54	$111,178.98