AN ABSTRACT OF THE THESIS OF

Yue Ke for the degree of Master of Science in Applied Economics presented on June 4, 2015.

Title: Economic Analysis of A Road Usage Charge

Abstract approved: ______________________________

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This study evaluates the distributional impacts of an alternative public roads finance method, a road usage charge (RUC) fee, on lower income households and rural households in Oregon. While previous research has relied on the 2001 and 2009 National Household Travel Survey (NHTS), this research will uses the 2011-2013 Oregon Household Activity Survey (OHAS) data. The OHAS dataset is used to assess the impact of changing from a 30 cents per gallon fuel tax to the 1.5 cents per mile RUC as proposed in SB 801, and to examine regional differences in driving behaviors that may be relevant in further assessing the impacts of a change in policy. Results show that overall the RUC will be slightly more regressive than the fuel tax, but that impacts may vary due to regional differences in the determinants of vehicle miles traveled (VMT).

Economic Analysis of A Road Usage Charge

by

Yue Ke

A THESIS

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Master of Science

Presented June 4, 2015
Commencement June 2015

Master of Science thesis of Yue Ke presented on June 4, 2015.

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ACKNOWLEDGEMENTS

This research was funded by the Furman Fellowship in Transportation Economics. I would also like to thank the members of my cohort for helping me survive the first year, and friends and family for their support.

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Chapter 1: Introduction

Revenues produced by state and national gas taxes have been increasingly unable to keep up with the costs of maintaining and expanding the road system[1]. This funding deficit has led state and national departments of transportations to seek funding sources other than user fees, including taking on debt to pay for road maintenance and construction, reallocating revenues from property taxes, sales taxes, bond finance, etc. (Kile, 2011; Wachs, 2013). Recognizing this financial shortfall, the National Surface Transportation Infrastructure Financing Committee (2009) recommended the use of a road usage charge as a possible policy tool to help provide sustainable funding. In Oregon, the state legislature formed a task force to study the issue of highway finance; their recommendation was to assess a mileage based fee for light vehicles (Whitty, 2007).

At the same time, national legislation such as the Federal Surface Transportation Policy and Planning Act of 2009 (which includes policy goals such as greenhouse gas (GHG) emissions reductions and increased use of public transit) as well as Oregon state legislation mandating GHG reductions of 75% below 1990 levels by 2050, expects the transportation sector to play a pivotal role in achieving these goals (Com-

[1] The state of Oregon has long been a pioneer in implementing transportation revenue collection programs. In 1919, Oregon was the first state to introduce a fuel tax to finance highway expenditures and the Federal government followed with a federal fuel tax in 1932. Heavy trucks–those that weigh more than 26,000 pounds–have been subject to weight mile taxes rather than fuel taxes since 1948. While Oregon raised the fuel tax in 2011 from the 1993 rate of 24 cents per gallon to 30 cents per gallon, the additional revenues did not meet state department of transportation needs.

merce Committee, 2009; Dingfelder et al., 2007).

While the shifts in passenger vehicle fleet composition have helped meet national and state goals of carbon emissions reduction and reduced dependence on foreign oil, it has also led to a disassociation between road use and fuel consumption. As the pace of development of hybrid electric and pure electric vehicles has increased, these vehicles are expected to continue to gain market share as they become more affordable (Gartner, 2012; Shahan, 2013). High fuel efficient and hybrid vehicles require less fuel to travel the same distance as vehicles employing older fuel-usage technology; electric vehicles require no fossil fuels to travel the same distance. Perversely, the reduced operating costs per mile to drivers of more fuel efficient vehicles can cause a rebound effect, increasing miles driven and the associated damage to roads, furthering weakening the link between fossil fuel taxes and vehicle miles traveled (Small and Dender, 2007; Greening et al., 2000; West, 2004; Goldberg, 1998). Because road damage from hybrid and electric vehicles are similar to that of less fuel efficient vehicles, the gas tax is no longer a reliable or equitable second-best road user fee.

In Oregon, the first task force that convened to study road usage charges (RUCs) was established in 2001, and pilot RUC programs were conducted in 2007 and 2013. The first pilot was largely a proof-of-concept technology test. In the second pilot Oregon DOT sought to align its program with public preferences identified from the previous pilot, including addressing citizens' privacy concerns (Whitty, 2013). Drawing on the successful pilot programs and promising research, Oregon Senate Bill 810 (SB 810) passed both chambers with bipartisan support and was signed into law by Governor Kitzhaber in 2013.

SB 810 creates a program that allows for drivers to pay a flat rate per mile of 1.5 cents in lieu of the state fuel tax (Hansell et al., 2013). This would serve to replace the current fuel tax. The first phase of this program includes a 5,000 vehicle pilot study, scheduled to start on 1 July, 2015. There is some concern that it will be regressive and could have an adverse impact on households in rural areas (Whitty, 2013).

The OHAS differs from NHTS in several major ways. First, as opposed to the national dataset, it consists of 19,932 Oregon households whereas the NHTS was a national data set and included 339 Oregon households. Unlike the NHTS, which was collected for transportation research needs, the OHAS was conducted primarily to assist state and municipal planning activities. As the OHAS was collected more recently than the NHTS, newer vehicle technologies including hybrid and electric vehicles are better represented although they are still a small percent of the total vehicle fleet.

This paper is organized as follows: The next section will be a review of relevant literature followed by a discussion of the methodology to be used in this study. Section three will introduce the OHAS data set and discuss its advantages and limitations. Section four will present static model results as well as provide specifications of dynamic models and results. The final section will conclude with key findings, limitations of the results, and recommendations for further inquiry.

Chapter 2: Literature Review

Nationwide, there have been numerous studies on mileage-based fees. Accordingly, the terminology in literature differs slightly. Depending on the author, they are called mileage based user fees (Baker, 2008; Zupan, 2012), road user charges (RUC) (D'Artagnan, 2013; Hansell et al., 2013), vehicle miles traveled (VMT) taxes (McMullen et al., 2010), and VMT fees (Kile, 2011; Zhang et al., 2009). This research uses the term RUC in order to stay consistent with language used in SB 810.

The adoption of VMT fees as a RUC mechanism is somewhat controversial. Evidence from pilot studies suggests that VMT fees are more transparent than fuel taxes, and may lead to a reduction in VMT as households are better able to gauge the true cost per mile of driving (Whitty, 2007; Munnich, 2011).

There are four main objections to the adoption of a RUC: 1) Privacy concerns that a government agency is tracking the activities of consumers; 2) Concerns that a RUC will increase costs for rural households relative to urban households; 3) Concerns that a RUC will increase the regressiveness of highway finance; and 4) Concerns that a RUC will induce households to use fuel inefficient vehicles in the short run (Whitty, 2013). The privacy concern surrounding VMT fee adoption is a technological problem that has been addressed in pilot studies across the nation (Whitty, 2007; Hanley and Kuhl, 2011). Concerns over the possible rebound effects in households choosing to use fuel inefficient vehicles in the face of a RUC scheme have not been studied due to a lack of data as large scale RUCs for household personal vehicles have never been implemented. However, Zhang et al. (2009) finds that changes in the user fee structure of the magnitudes examined by this study are unlikely to affect vehicle choice as fuel taxes are such a small component of the per mile cost of driving relative to the fuel cost savings per mile from using more fuel efficient vehicles. Accordingly, this research focuses on addressing the income and regional impacts of RUCs.

Previous research on RUCs can be broadly divided into four categories: studies on the public's perception, survey studies produced for various state departments of transportation interested in replacing the state fuel tax with a RUC, studies using the NHTS dataset studying possible distributional effects of RUCs, and results from pilot programs implementing RUCs.

Economists and policy makers typically consider the fossil fuel tax as regressive for low income households. Because all drivers regardless of income levels are assessed the same per gallon fuel tax, the percentage of income for lower income individuals that the fuel tax deducts is larger than the corresponding share for an individual receiving a higher income. Additionally, lower income households tend to drive older, and therefore less fuel efficient, vehicles. This implies that they have to purchase fuel more frequently than wealthier households, causing a fuel tax to be even more regressive. When examining expenditure data or lifetime income proxies however, the degree of regressivity lessens (Poterba, 1991). The US Congressional Budget Office (1990) finds that the fuel tax is regressive relative to annual income but general proportional to total expenditures. Poterba (1991) finds that the gas tax is actually slightly progressive over the bottom half of the lifetime income distribution. Rogers

(1995) finds that fuel tax burdens rise over the bottom three lifetime income quintiles and fall thereafter. Chernick and Reschovsky (1997) find that average fuel tax burdens in the intermediate run are only slightly less regressive than annual income burdens, due to the limited degree of income mobility over the time period.

RUCs are relatively new policy instruments that have yet to be implemented on a national or state-wide scale. Policymakers are interested in the public's acceptability towards per mile charging. While numerous public opinion polls have been conducted, many share outcomes regardless of national or state specific scopes of study (Agrawal and Nixon, 2009; Agrawal and Nixon, 2014; Nordland et al., 2013; Hanley and Kuhl, 2011; Weinstein et al., 2006; Whitty, 2013). Typically the less the public knows about a hypothetical RUC, the more they are against its adoption; upon receiving educational materials or participation in focus groups, the public tends to be more accepting of the RUC. Upcoming NCHRP research by A. W. Agrawal will assess the body of public opinion research on RUCs.

Qualitative research based on interviews and focus groups at both national and state-wide levels have yielded similar results as well (Agrawal et al., 2011; Whitty and Imholt, 2005; Munnich, 2012; Baker et al., 2008; Ungemah et al., 2013). Overall, the less the public knows about a RUC's details, the more they tend to oppose implementation of a RUC. If the public is educated about how a RUC system works, their approval rating tends to increase. A common concern from the qualitative research indicates the aspect of government intrusion via tracking devices (i.e. loss of privacy) as be the main reason most people oppose a RUC (Whitty, 2013). Other concerns included the perceived regressive nature of a RUC on lower income households. Qualitative research in Oregon indicates that rural households fear they would pay more with a RUC than a fuel tax as they must drive further distances to reach certain goods and services, ceteris paribus; however rural households' travel behaviors suggest that they make fewer trips on average than urban households, which may ameliorate the burden of RUC fees (Whitty and Capps, 2013; Whitty, 2007; D'Artagnan, 2013). Quantitative research supports this as well, with evidence showing that rural households drive less fuel efficient vehicles on average than do urban households (McMullen et al., 2010). However, the distinctions between "urban," "rural," and the spaces in between may not be easily defined (Crandall and Weber, 2005).

Public opinion surveys show that many Oregonians believe that lower income households and households in rural areas would be the "losers," facing higher fee incidences than higher income households and urban households (D'Artagnan, 2013): Lower income households, by merit of earning less annual income, would also expect to pay a higher percentage of their incomes to a RUC fee compared to wealthier households. However, because low income households tend to drive older, and thus, less fuel efficient vehicles, their losses in a RUC system may be offset in the short to medium runs by not having to pay fuel taxes (Zhang et al., 2009). Additionally, a New York State DOT study described RUCs as possibly being less regressive in the long run than a fuel tax because lower income households tended to drive less than higher income households; however, no empirical evidence was presented to support this claim (Zupan et al., 2012).

While qualitative studies reveal how the public views RUC systems and the implementation challenges faced by policy makers, they fail to depict how people actually behave under such systems. Pilot programs, which allow transportation agencies to experiment with technological solutions as well as implementation designs, tend to be limited in scope and scale, as they tend to have limited funding resources and are designed to test specific technology applications. Additionally, their results suffer from a self-selection bias as participants are volunteers who are potentially more likely to change their behavior than the general population.

Most pilot programs contained less than one hundred participants. Because of the small sample sizes as well as possible biases due to voluntary participants, researchers have largely been unable to rely on pilot results as data for empirical work on the distributional impacts RUC implementations have on various populations. The majority of empirical work that has been done uses the 2001 or 2009 NHTS data set to predict the effects RUCs would have on household behavior (Weatherford, 2011; Kastrouni et al., 2012). State specific RUC studies using the NHTS face an additional challenge of having small sample sizes to work with. A common technique has been to use bolster the sample size by including households from additional states that share population densities, demographics, and driving patterns(Paz et al., 2013; Zhang et al., 2009).

Zhang et al., (2009) examine the short and long run distributional impacts that could arise in a RUC scheme using 2001 NHTS data. The research finds that the average rural household benefits in the short run from the adoption of a VMT fee despite driving more miles than its urban counterparts, as the rural vehicle fleet is made up of more fuel inefficient vehicles. Long run distributional effects between income groups are found to be minimal, as all income groups would pay slightly more for road use, between $1.57 and $5.03 more annually. Rural households on average would pay slightly more than the average urban household per year in the long run. McMullen et al. (2010) find that urban households would pay slightly more under a RUC while rural households would pay slightly less in Oregon. A flat VMT fee was found to be slightly more regressive than the fuel tax. Alternative RUC structures that incentivize the use of fuel efficient vehicles are found to have a larger negative impact on low income households than a flat VMT fee (McMullen et al., 2010).

Weatherford (2011) analyzes the distributional implications of a RUC in lieu of the federal fuel tax using data from the 2001 NHTS. He finds that VMT fees are less regressive than fuel taxes, and the burden of the tax shifts from low income households to high income households. His results also indicate that the tax burden will additionally shift from rural to urban households. However, a disaggregated analysis of low income households show that a RUC will have negative implications for low income urban households and positive implications for low income rural households. Despite this, Weatherford (2011) finds that the annual change in tax burden for 98% of the population is less than $20.

Paz et al., (2013) uses the NHTS data for Nevada and states with similarly low population densities, including Arizona, Utah, Colorado, Idaho, Montana, Wyoming, and New Mexico. The research finds weak evidence that while both urban and rural households would drive less with a RUC, rural households would incur slightly higher annual costs compared to their urban counterparts. However, the data's small sample size meant it was difficult for Paz et al. to arrive at any consistent conclusions regarding the impact a RUC may play on various income groups.

Depending on the area being studied, wealthier households may drive more or less than lower income households. Similarly, whether or not owning a fuel efficient vehicle deters households from driving seems to depend on which state is being considered. Using the Iowa subset of NHTS data, Kastrouni et al. (2012) find that households with fuel efficient vehicles drove more miles annually, suggesting that the rebound effect is in evidence. Consistent with previous research, wealthier Iowa households drove more than lower income households. Paz et al.'s (2013) research on RUC fees in Nevada using the 2009 NHTS data subset shows that wealthy households drove less than poorer households, due to the possibility of working from home increasing for jobs associated with higher salaries. Contrary to the rebound effect literature and Kastrouni et al.(2012), Nevada households with fuel efficient vehicles drove less than those with fuel inefficient vehicles.

Larsen et al. (2012) uses an expanded Texas data from the 2009 NHTS to evaluate equity implications from possible RUC schemes. Rather than determining Texas-specific price elasticities for VMT demand, they rely on Wadud et al.'s (2009) national fuel price elasticities of VMT demand. They find that a RUC would be at least as regressive as gas taxes, if not more so. However, a criticism of applying externally determined elasticities can be found in Kastrouni et al (2012) in which development of distinct local models–and therefore locally calculated elasticities–are deemed necessary for the evaluation of distributional impacts.

Besides the distributional effects on low versus high income households, researchers are typically also concerned with the distributional impact a RUC would have on rural versus urban households. Thus, distinguishing urban from rural is a nontrivial task with important policy implications.

In the Oregon context, the extremes of urban, such as downtown Portland, and rural, such as Steens Mountain, are easily classified; however, classification of other locations is more ambiguous. Crandall and Weber (2005) examine four classification systems and demonstrate how the demographic profile of rural Oregon changes as definitions of rural change. They suggest eschewing national schemes such as those devised by the US Census Bureau, Office of Management and Budget, and the USDA in favor of an Oregon specific classification scheme. Their proposed five tiered classification system is similar to the one used in the OHAS data.

As RUC fees have attracted attention as an alternative method of financing federal and state DOTs, much research, both at the state and federal levels, has been done. Researchers typically rely on the either the 2009 or 2001 National Household Travel Survey (NHTS) for data (McMullen et al (2010); Zhang et al (2009); Weatherford 2011; Kastrouni et al., 2012; Larsen, 2012; Paz, 2013). The NHTS is a national dataset collected by the Federal Highway Administration and contains only a few hundred samples for each individual state. While state DOTs can request that additional households to be surveyed most opt out due to costs. In order to bolster sample size, studies that focus on the potential impacts of RUC adoption have to group additional states as being similar to the state under study on a set of econometrically determined criteria (McMullen et al., 2008; Zhang et al., 2009).

Within the NHTS, households are categorized as urban or rural based on the 2000 US Census criteria. Using these definitions for rural and urban, researchers agree that under the current fuel tax system, rural households tend to drive more miles than their urban counterparts (Zhang et al., 2009; Kastrouni et al., 2012; Paz et al., 2013; Weatherford, 2011). In the short run, most researchers find that the average rural household stands to gain more from the adoption of RUCs than urban households, perhaps due to rural vehicle fleets being made up of more fuel inefficient vehicles (Zhang et al., 2009; Weatherford, 2011). In the longer run however, Paz et al. (2013) and Zhang et al. (2009) finds that rural households in their respective study areas would shoulder more of the tax burden. Zhang et al. (2009) suggests that this may cause rural households to prefer even more fuel inefficient vehicles when under a RUC system than the current fuel tax system. However, Paz et al. (2013) argues that rural households will reduce their vehicle miles traveled in response to RUC implementation. Weatherford (2011) finds evidence on the contrary, and suggests that the tax burden will shift from rural to urban households. However, the NHTS dataset does not include every household's actual location; researchers are unable to refine its urban/rural categorization for an even more geospatially disaggregated analysis. Furthermore, because the NHTS relies on the 2000 census, its rural/urban definitions may be outdated. In the last 15 years, many areas across the country have experienced growth, and formerly rural areas are now considered urban.

Similar to the Kastrouni et al. (2012) findings that location specific models should be developed to evaluate local changes due to implementing a road usage charge, research on the determinants of vehicle miles traveled demand suggest that determinants are site specific. The existing literature is in disagreement over the link between VMT and economic activity. Puentes and Tomer (2008) argue that factors such as telecommuting and online retail activities which provide substitutes for mobility, and increased availability of public transit weaken causal links from VMT to GDP. However, Pozdena (2009) is concerned by the possible adverse impacts to economic activity by VMT reduction policies. McMullen and Eckstein (2013) find that VMT determinants differ across different sized urban areas and thus VMT reduction policies have different impacts in different locations.

In their study of VMT in 87 US cities over the period 1982-2009, McMullen and Eckstein (2013) find that fuel price, transit use, and population density are negatively related to VMT per capita. Per capita VMT is found to differ significantly across regions, and the industry mix of urban areas have a significant impact on driving behaviors. However, because every urban area studied had slightly different industry mixes, McMullen and Eckstein suggest that policy makers avoid one-size-fits-all type VMT reduction policies (2013).

Just as most of the literature studying road usage charges uses the same dataset, the 2001/2009 NHTS, they also employ similar models. With the exceptions of Kastrouni et al. (2012) who use a 3SLS dynamic model and Zhang et al. (2009) who use a discrete choice model for long run effects, the extant literature uses a static model to predict short run effects of RUC implementation and an OLS-based dynamic model to predict medium term effects. The following section discusses methodologies used in the literature that are relevant to this research.

Chapter 3: Methodology

In the short run, households may not be able to change their behavior in the face of a price change. This means that even if the price of driving changes due to a change in fuel taxes or a shift to a road usage charge, households cannot respond by decreasing or increasing the number of daily miles driven right away, although in the medium or long run they can adjust their behaviors accordingly. A static model can be useful for analyzing short run effects a RUC has on weekday household travel expenditures in the short run. The static model tends to overestimate the effects of an increase in price per mile traveled as households are not allowed to reduce their VMT, as standard microeconomic theory suggests would happen for downward sloping demand curves. As its name implies, this model assumes households drive the same vehicles for the same distances both before and after a RUC is imposed. In other words, under the static model, all households are assumed to have a price elasticity of demand of zero.

The static model used in this research is calculated following the methodology of McMullen et al. (2008). Using household daily VMT and the average household miles per gallon fuel efficiency rating, one is able to determine the number of gallons of gasoline consumed by the household for travel purposes.

$$Gallons = \frac{HHVMT}{HHMPG} \tag{3.1}$$

Because households reported the price of fuel on the day of the survey, total household expenditures on fuel can be found by multiplying the price of fuel per gallon by the number of gallons consumed.

$$Exp_{gas} = Gallons * Price_{gas} \tag{3.2}$$

In order to calculate the price of traveling the same mileage under a RUC, one must determine how much each household paid for fuel without the fuel tax, and add the per mile RUC fee for each mile traveled.

$$Exp_{RUC} = Gallons * (Price_{gas} - Tax_{gas}) + HHVMT * Tax_{RUC} \tag{3.3}$$

The net change by households is the difference in household expenditures on daily miles traveled, going from a fuel tax to a road usage charge.

$$\Delta_{static} = Exp_{RUC} - Exp_{gas} \tag{3.4}$$

As the static model's underlying assumption of no behavior change ignores possible household demand responses to the change in tax schemes, a dynamic model allows for more appropriate impact analyses. Aspects of the model considered "dynamic" include changes in the usage and relative usages of existing household vehicles due to adoption of a RUC. Short run household responses may include changing trip routes, vehicle occupancies, adjusting trip frequencies, and considering alternative modes of transportation. Long run household responses may include altering the household vehicle fleet by either purchasing a more fuel efficient vehicle or retiring a current vehicle, relocating to a areas closer to frequently traveled to trip destinations, or moving to areas better served by public transit. However, due to limitations in the OHAS data, we are unable to estimate dynamic models that are robust enough to calculate impacts.

In particular, the dataset contains only weekday household VMT data. As one cannot infer a household's annual VMT from a single day's worth travel data, the OHAS does not provide the data necessary for estimating robust dynamic models similar to those found in other studies relying on the NHTS. Also, many vehicles were not driven on the day of the survey. Without annual miles traveled per vehicle data, it is difficult to determine how households make vehicle substitution decisions. If the magnitude of a household's actual price elasticity of demand is large, then the static model will overstate the impact of a RUC; if the magnitude of the household's actual price elasticity of demand is small, then the static model will be a good approximation of the real impact. A household's price elasticity of demand is likely to depend on regional differences not captured in the OHAS including the availability of alternative modes of transportation, the ease of mode switching, etc. However, McMullen et al. (2008) find little quantitative difference between static and dynamic results of the impact using the NHTS data set for Oregon, so we focus on the static impacts here.

Ordinary least squares regression methods are used in this study to further explore determinants of VMT in Oregon that will help policymakers recognize geographic differences in household driving behavior. More complex econometric methods (two-stage least squares, mode choice models, etc) are not feasible as the dataset lacks the additional data required. Furthermore, this research is solely concerned with driving households. Households that did not own vehicles and therefore could not drive were dropped from the dataset. Additionally, households that reported not driving on the day of the survey were dropped from the dataset. Because the research assumes that all households demand some positive amount of VMT, a probit model cannot be used. While beyond the scope of this research, a probit estimation might yield insight into household mode choice decisions, such as whether to use a private vehicle or take public transit.

Multi-stage least squares modeling has infrequently been done in the past (Kastrouni et al., 2012). However, it assumes that there are endogeneity and bias problems. There is some disagreement over whether or not vehicle miles traveled demand is endogenous to household income and gross domestic product (Pozdena 2009). However, the majority of research suggests that while correlation between VMT and economic activity exists, causal relationships do not (McMullen and Eckstein, 2012; Litman, 2013). Additionally, the OHAS dataset does not contain variables that could be used as instruments. Thus, it was decided that multi-stage least square estimates were unnecessary. As the OHAS is cross-sectional in nature, fixed effects estimation was also not possible.

The basic regression model used in this research is shown in equation (3.5). According to basic economic theory, price per mile of travel and household daily income are included. As interaction terms are not included in the model specification, the coefficients of variables can be used directly as elasticities. Elasticities of dummy variables are calculated using the formula $\dfrac{1}{1-e^{\beta}}$.

$$ln(HHVT) = \beta_0 + \beta_1 ln(dayINC) + \beta_2 ln(ppm.gas) + \mu \tag{3.5}$$

$ln(HHVMTgas)$ = natural log of household VMT under gas tax

$ln(dayINC)$ = natural log of daily income

$ln(ppm.gas)$ = natural log of price per mile under gas tax

The basic model is improved upon by adding a vector of household characteristics, vehicle substitution dummies, and household location type and household geospatial location dummies (3.6). While previous researchers use a similar model based on McMullen et al. (2009) and Weatherford (2011), these last two categories of dummy variables are unique to this research and dataset. The research additionally examines whether or not the results are affected by households' geographic locations and location types. This allows us to recognize the importance of recognizing location specific differences in VMT behavior when formulating policy as noted by Kastrouni et al. (2012) and McMullen and Eckstein (2013).

$$\begin{aligned} ln(HHVMT) = \beta_0 + \beta_1 ln(dayINC) + \beta_2 ln(ppm.gas) + \beta_3 \mathbf{HH} + \beta_4 \mathbf{SUB} + \\ \beta_5 LOCTYPE + \beta_6 Region + \beta_7 MPO + \beta_8 ln(HHVEH) + \mu \end{aligned} \tag{3.6}$$

HH = vector of household attributes including number of workers, number of students in the household, and the log of the total number of people within the household

SUB = vector of vehicle substitution dummies, including if household owns more than one vehicle type and if a household owns a hybrid or electric vehicle

$LOCTYPE$ = Dummy variables for each of the five household location types based on proximity to population density limits as defined in the OHAS dataset

MPO = Dummy variables for each of the 9 MPOs in Oregon

$Region$ = Dummy variables for each of the 8 geographic regions in Oregon

$HHVEH$ = number of household vehicles

All other variables are same as previously defined.

Prior researchers have primarily used NHTS data. As previously mentioned, this research uses the OHAS dataset instead. The differences in these two datasets have contributed to the slightly different model specification outlined above. The next section will take a closer look at the OHAS dataset and discuss its advantages and limitations.

Chapter 4: Data

The data used for this study is the 2013 Oregon Households Activity Survey (OHAS) dataset collected by Oregon Department of Transportation (ODOT) between 2011 and 2013. This section introduces the data used in the research, compares it with datasets used in other studies, and discusses the steps taken in turning the raw data into a usable dataset are then discussed. An examination of the geospatial aspects of the data follows. Next is an analysis of the data's time dimension, as the OHAS was collected over a multi-year period as well as on different days of the week. Household vehicle miles traveled (VMT), fuel efficiency, and household income variables' calculations are defined. This section ends with a short discussion of the differences between the OHAS and the NHTS, as well as the derivation of dummy variables.

The OHAS was designed to help state and local planners deal with a diverse set of transportation related issues, such as public transit services in Rogue Valley and expanding biking infrastructure in Portland Metro. It contains responses from 19,932 households, including over forty thousand individuals. Although it is a recent dataset, the number of electric vehicles (EVs) captured is statistically insignificant–just 34 of the over 41,000 vehicles were electric (Chen, 2013). The number of hybrid and alternative fuel vehicles is also low–631. Within the raw data, the mean fuel efficiency is 23 mpg, while the median is 22 mpg.

4.1 Data Cleaning

First, the data was cleaned to remove non-Oregon households, households that do not own any vehicles, oversampled households, and non-driving vehicle owning households. Because it was conducted for transportation planning, commuters from Clark County, Washington were also captured in the survey. As this research is only concerned with a change in the price of driving for Oregonian households, these 1,667 Washington households were removed. Further examination of the dataset revealed one household in California. It was also omitted from the dataset.

For the most part, households were randomly chosen to participate in the OHAS survey. Not all households own a vehicle. Retaining these 826 Oregonian households surveyed that reported not owning a vehicle in the data is problematic. As this research seeks to explore the effects of a change in welfare based on a change to the price of driving, regardless of whether a mileage based user fee or a gas tax was in place, households that do not own vehicles are not expected to be affected. Thus, these 826 households are removed from the dataset.

Intentional oversampling of certain locations (e.g. Portland metro, with respect to bicycle miles traveled) occurred in order to give policy makers a better picture of what specific situations looked like. The Texas Transportation Institute was contracted in 2013 to reweight the dataset to conform to 2012 American Communities Survey (ACS) household statistics. The reweighting process identified the oversampled households and assigned weights of zero, and assigned weights greater than zero for other households so that overall, household demographics match that of the

ACS.[1] [2] This research only uses the zeros to remove the 272 oversampled households.

After removing the intentionally oversampled households, the amended OHAS dataset contains 17,166 households that own at least one vehicle. As the OHAS asked respondents to estimate the number of miles traveled on the day of the survey, the household's reported mileage for the survey day may not be representative of that household's average daily VMT demand. In the case of the 1,765 zero mileage households that own at least one vehicle, this is likely the case. In order to account for these zeros, a regression could be run on households with VMT larger than zero to determine coefficients. These coefficients could then be used to impute household VMTs for the zero reported VMT households (Gillingham, 2012). However, this research will forgo such a process as it does not add much in additional explanatory

[1] Although every household was assigned a weight, household weights greater than zero are not used in the research. The weights were designed to allow households in the OHAS to conform to 2012 ACS households based on a vector household attributes. When interested in a household's behavior change in the face of a changing price per mile, the deflation or inflation of actual miles traveled due to an application of weights is inappropriate. For instance, if a household with a certain set of characteristics is over-represented in the OHAS compared to the ACS, it might be assigned a weight of 0.5. The application of the 0.5 weight to this household's VMT would lead to only considering half of the actual miles traveled. Similarly, if a certain type of household is found to be under-represented in the OHAS when compared to the ACS, it may receive a weight of 8.0. Applying this weight to a household's daily VMT implies that the household traveled 8 times as much as it actually did. A more logical approach would be to increase or decrease the number of households. For instance, if a household received a weight of 8.0, then seven identical households, in terms of household demographic attributes and location attributes, could be created. Likewise, if a household received a weight of 0.5, a second identical household could be removed from the dataset. However, for households receiving weights of irrational numbers, this matching and adding/removing households method can be problematic if the requisite number of identical households to be removed do not exist. Therefore, the research decides to ignore the weights entirely.

[2] The implication of not using weights is that the RUC static model's impact results only pertain to the households represented in the OHAS. In other words, because the data was not weighted to conform to the known universe of Oregon households as expressed in the ACS, static results from this research can not be directly applied to households not captured by the OHAS. However, because the OHAS randomly sampled a large number of households, the lack of weighting should not OLS results.

power given the remaining sample of 15,401 households is still a relatively large number of observations. In this research, the 1,765 nondriving vehicle owning households are instead removed from the dataset.

During the verification of vehicle VMT numbers, it was revealed that 2 vehicles had over 1500 miles traveled during the survey day. Regarded as outliers or possible data entry errors, these vehicles' VMTs were removed from the data by being assigned NA's. The two vehicles that recorded traveling more than 1500 miles may have been incorrectly inputted during the data collection phase. The maximum daily vehicle miles traveled range was set at 1500 miles because it is barely feasible if a person spent an entire day driving on an interstate highway. Given that the state of Oregon's rough dimensions are 400 miles by 360 miles, some of this driving would likely occur out of state. Depending on a household's technology preference, they may or may not be billed for out-of-state miles under a RUC system. However, the raw data did not include when households crossed state lines during inter-state trips, nor does it include household technology preferences. Thus, the vehicle VMTs of values less than 1500 were included in the data.

4.2 Geospatial Aspect of Data

The remaining Oregon households are divided into either metropolitan planning organizations (MPOs) or regions. As shown on Figure 4.1, seven regions have been established–Coast, Deschutes, East, Mid Willamette Valley, North Central, North Willamette Valley, Southern Valley, and South Central. ODOT experts believe

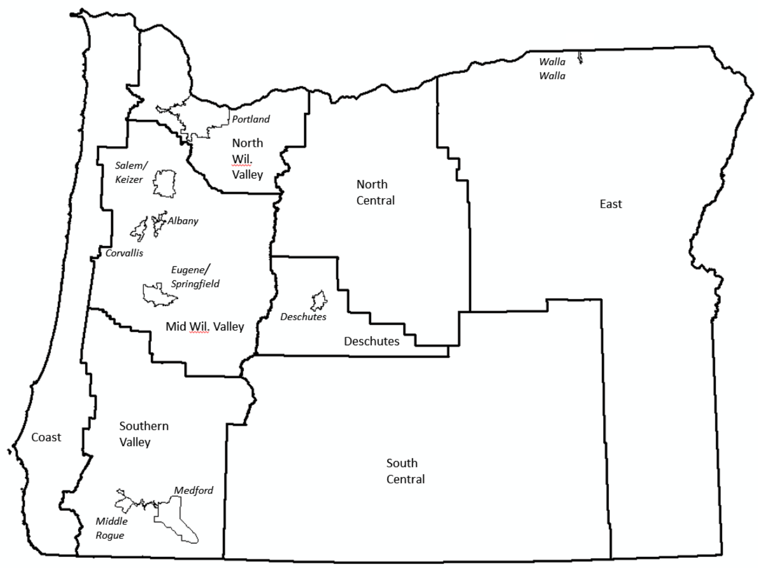

Figure 4.1: Geographic Regions and MPOs in Oregon

that these regions are a better way of dividing up the state into unique subareas compared to simply using an East Oregon-West Oregon or urban/rural bifurcation (Whitty, Jim. 9 March, 2015. TAC Meeting). For instance, Deschutes county households may behave differently from other households due to their distance to Bend MPO. Isolated city households may behave differently if they are part of coastal communities rather than a part of towns along the I-84 corridor. It is important to note that the ODOT regions do not strictly follow county lines. The nine state-recognized MPOs are also marked on the map with their respective names in italics. These include Albany, Bend, Corvallis, Eugene-Springfield, Portland, Medford, Middle Rogue, Salem-Keizer, and the Walla Walla Valley. All households are assigned regions. Thus, Portland MPO households also belong to North Willamette Valley. Households in Albany, Corvallis, Salem/Keizer, and Eugene Springfield MPOs are also in the Mid Willamette Valley region. Likewise, households in Medford and Middle Rogue MPOs are flagged as being in Southern Valley, and all households in Bend MPO are in Deschutes region as well. Households that do belong to any MPOs are given NA values for their respective MPO variable.

Specific to this dataset, each household has also been assigned a location type variable based on proximity to population density criteria. These location types are similar to the Oregon specific rural-urban spectrum proposed by Crandall and Weber (2005). This location type classification allows for households that reside within MPO jurisdictional boundaries to receive a location type that is not MPO, particularly if they are located on the MPO's outskirts. Likewise, households may receive a location type code of MPO despite not belonging to an actual MPO.

For a household to be considered rural, it must take more than two miles to accumulate 2,500 people, and more than 15 miles to accumulate 50,000 people. Households are coded as being in an isolated city if it takes less than two miles to accumulate 2,500 people but more than 15 miles to accumulate 50,000 people. Rural near major center households are those that require more than one mile to accumulate 2,500 people but less than 15 miles to accumulate 50,000 people. City near major center households are less than one mile away from accumulating 2,500 people and less than 15 miles to accumulate 50,000 people. MPO households are those that require less than one mile to accumulate 2,500 people and less than 5 miles to accumulate 50,000 people. Population density data comes from the US Census Bureau's American Communities Survey. Figure 4.2 provides a visual guide to this data. Darker shaded dots indicate increasing levels of urbanity according to the five tiered location type categorization system.

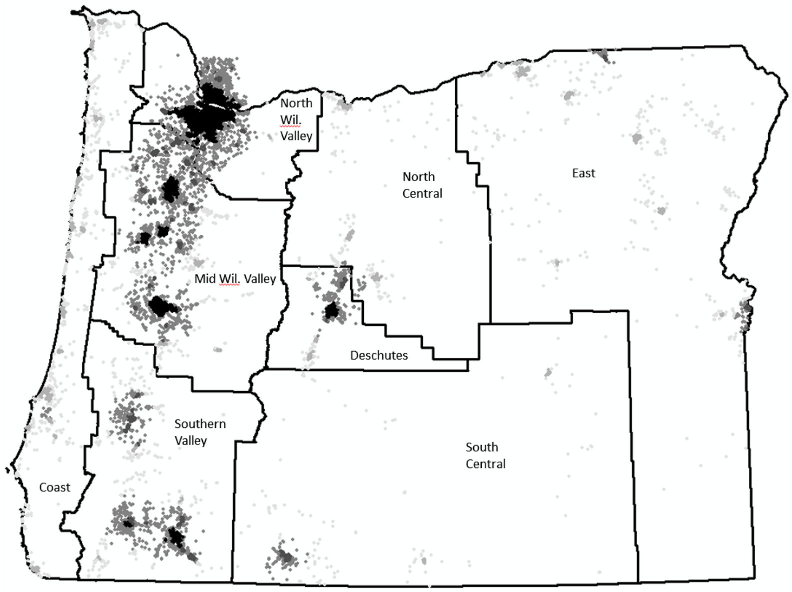

Figure 4.2: Distribution of Household Location Types in Oregon

The darker dots in Figure 4.2, denoting households that have a location type of MPO or city near major center, mostly line up with MPO boundaries in the first map. Notable exceptions are the large clusters of light dots where the towns of Roseburg, Klamath Falls, and Ontario lie.

4.3 Temporal dimension of data

The OHAS dataset is cross sectional in nature, and captures only the VMT demand for the day of the survey. While other datasets including the NHTS provides estimates for annual VMT by households, the OHAS dataset lacks additional information required to do so. Seasonal variability in travel behavior within a household was not captured. As the surveys were administered solely on weekdays, weekend travel behavior was not recorded. Discussions with ODOT and others indicate that annualizing VMT is beyond the limits of the data (A. Bettinardi, personal communication, December 12, 2014). Therefore daily VMT estimates are used for this research.

One of the concerns with this type of dataset is that it may not be evenly spread across days of the week. Kuhnimhof and Gringmuth (2009) find that day to day variation in travel behavior within a household is an important determinant of VMT. Table 4.1 shows that state-wide, the OHAS data is evenly distributed across days of the week within each survey area. There is only a percentage point or two in differences between days. The largest percentage point difference is the seven percentage points between Tuesday and Friday survey numbers in Bend; however, as the total number of surveys is only 789, this is not a large difference in numbers. There appears to be no other systemic poor distribution of survey responses.

Table 4.1: Distribution of all survey responses by day surveyed (shown in percentages)

	Monday	Tuesday	Wednesday	Thursday	Friday	Total Number
Oregon State-wide	21%	21%	20%	19%	19%	17,166
Coast	20	20	20	20	19	1,387
Deschutes	20	23	19	20	18	1,134
East	21	21	19	19	20	1,143
Mid Wil. Valley	20	20	21	20	20	6,071
North Central	18	24	19	22	17	382
N. Wil. Valley	22	22	20	19	18	4,268
Southern Valley	21	21	22	18	18	2,280
South Central	22	17	19	20	22	501

As previously stated, seasonal variability in travel behaviors within a household was not captured. However, if the dataset is large enough and evenly distributed between seasons within survey areas, inferences could still be made regarding seasonal travel variation. Tables 4.2 and 4.3 shows the number of surveys conducted by year and season, respectively, for all households.

Table 4.2: Distribution of all survey responses by year (shown in percentages)

	2011	2012	2013
Oregon state-wide	48%	17%	35%
Coast	100	-	-
Deschutes	30	-	70
East	-	100	-
Mid Wil. Valley	72	28	-
North Central	100	-	-
N. Wil. Valley	1	-	99
Southern Valley	55	-	45
South Central	90	10	-

Table 4.3: Distribution of all survey responses by season (shown in percentages)

	Winter	Spring	Summer	Fall
Oregon State-wide	6%	43%	10%	41%
Coast	41	46	8	7
Deschutes	-	75	25	-
East	-	31	-	69
Mid Wil. Valley	58	31	2	9
North Central	-	83	17	-
N. Wil. Valley	53	44	-	3
Southern Valley	32	46	9	13
South Central	-	80	14	6

Table 4.1 shows that the dataset is evenly distributed over the days of the week. Tables 4.2 and 4.3 indicate that the OHAS was primarily conducted in 2011 and 2013;

most households responded in the spring and fall months. This may be intentional on the behalf of enumerators. Due to possible bad road conditions in the winter months, overall travel may be lower than other times of the year. Summer months may have been avoided if vacation travel behaviors are seen to be a departure from normal or ordinary travel decisions. Furthermore, enumerators may have been constrained by budgetary or logistical considerations from being able to conduct the OHAS in a temporally consistent manner across all survey regions. Regardless, only weak inferences can be made regarding seasonal variability of travel behaviors.

4.4 Calculation of Variables

In its original form, the OHAS dataset was a relational database consisting of ten separate files indexed by SAMPN, each household's unique identification number. These files included data on household demographics, current and past vehicle ownership, trip and route data and additional spatial data on the household. Household demographic variables included the household size, number of workers, the number of students, annual household income in the form of income categories, racial identity information, and the number of licensed drivers. Unlike the NHTS, the OHAS did not report the number of children in the household; instead, the number of students is used as a proxy (however this is an imperfect proxy as it includes K-12 students as well as college students). As the OHAS was originally collected for aiding city and regional planning operations, it contained data that were not applicable to this research. Households reported the number of years they lived at their present address as well as their previous address, and gave reasons for moving. They also reported the number of phone and fax lines, as well as the type of Internet service received. In addition to the base OHAS questionnaire, city governments were also allowed to ask additional questions. For instance, Portland households were asked about attitudes towards bike services; Medford households were asked about public transit use. While data provided from these additional questions may provide insights relevant to this research, the decision was made to drop this from the final dataset because it existed for only a few MPOs.

One of the preliminary tasks was to create a dataset from the raw data. The trip and route data was used during the calculation of VMT by vehicle. These raw datasets included all trips by all household members during the day of the survey. In order to avoid over-counting household trips due to carpooling, only the subset of trips with drivers were evaluated. In this context, a trip is defined as going from a point of origin to a destination via a light-duty vehicle; public transit use, walking, and biking are intentionally omitted. This data was collected in feet. As a result, some small rounding errors may have occurred during the feet to mile conversion. Vehicle VMTs were summed by household to calculate household VMT variable, the primary unit of analysis.

Table 4.4 provides summary statistics of daily household VMT in miles of households that reported traveling on their respective survey days. As previously mentioned, because these are household miles traveled rather than individual's miles traveled, households with multiple drivers and vehicles may accrue large total VMT figures: therefore, the maximum miles driven by household column contains large numbers such as 1,179 miles and 1,110 miles, for North Willamette Valley and Deschutes, respectively. Because nearly half of the households surveyed reside in the Mid Willamette Valley or North Willamette Valley, the state-wide average is lower than the other regions' average miles driven would suggest. While the average daily miles driven by households in North Central was 56 miles, those households make up less than 3% of the overall OHAS sample. Average miles driven by households are generally much larger than the state-wide average for households in the Coastal, East, North Central, and South Central regions. This is consistent with previous research suggesting that households in rural areas must travel further to access the same services compared to urban households (D'Artagnan, 2013).

Table 4.4: Daily Household VMT (in Miles) by Region

	25% of all households drove no more than	50% of all households drove no more than	75% of all households drove no more than	Maximum miles driven by households	Average miles driven by households
Oregon State-wide	8	23	50	905	39
Coast	7	20	50	1,024	45
Deschutes	9	22	46	1,110	37
East	6	19	53	553	43
Mid Wil. Valley	8	23	51	852	40
North Central	10	34	76	905	56
N. Wil. Valley	8	25	48	1,179	35
Southern Valley	9	24	49	552	40
South Central	8	19	49	769	44

The following table shows the distribution of the omitted non-driving households by geographic location. Of the 1,765 non-driving households, just under a third lived in North Willamette Valley. This may be due to improved household access to public transit and closer proximity towards goods and services, compared to less urbanized areas around the state. Similarly, the 37% of non-driving households that lived in the Mid Willamette valley could also have better access to public transit, particularly if those households lay within MPOs such as Albany, Corvallis, Eugene/Springfield, or Salem/Keizer. As one would suspect, in more remote areas such as East, South Central, and North Central, where public transit is not as widespread and where goods and services may be spread out, there are much fewer non-driving households.

Table 4.5: Distribution of non-driving households (shown in percentages)

Total Households State-wide	1,765
Coast	6%
Deschutes	5
East	7
Mid Wil. Valley	37
North Central	1
N. Wil. Valley	32
Southern Valley	10
South Central	2

Additional relevant variables had to be calculated from the raw data. In order to find price per mile of driving either under a VMT fee or gas tax, a household's miles per gallon efficiency (mpg) number was generated. As vehicles have separate highway and city mpg ratings, their combined fuel efficiency ratings were used for simplicity. Households with a single vehicle were given that vehicle's mpg rating. Households with multiple were assigned a weighted mean of the combined mpg ratings of each driven vehicle became the household's mpg rating. Weights based on the percentage of a specific vehicle's VMT from the total household VMT was assigned to each vehicle's mpg rating, and summed. This method allows the data to show that households differentiated between vehicles.

$$HHMPG.wgt = \sum_{i=1}^{HHVEH} \frac{cmb_i}{vmt_i} \tag{4.1}$$

cmb_i = the EPA estimated combined city/highway mileage of vehicle i

vmt_i = Vehicle miles traveled by vehicle i

Arithmetic means of all household driven vehicles' fuel efficiencies were calculated as an alternative method for finding household mpg ratings.

$$HHMPG.avg = \frac{\sum_{i=1}^{HHVWEH} cmb_i}{HHVEH} \tag{4.2}$$

However, some households that reported owning vehicles in addition to the one(s) driven. A limitation to both mpg calculations is that they effectively assume that additional non-driven vehicles in a household's fleet do not exist. Table 4.6 contains summary statistics of the household weighted mpg ratings. Arithmetic mean household mpg ratings follow similar trends; for the sake of brevity, summary statistics are not shown.

From Table 4.6, the state-wide average fuel efficiency is between 21-24 mpg. Thus, a household mpg rating of less than 21 can be considered below average; a household mpg rating between 21 and 24 can be considered at the average; above 24 mpg can be considered above average. The households' mpg distributions by region using this rough approximation are shown in Table 4.7.

Table 4.6: Fuel Efficiencies of Driving Households (in miles per gallon) by Region

	Least fuel efficient household	25% of all households had at most	50% of all households had at most	75% of all households had at most	Most fuel efficient household	Average household fuel efficiency
Oregon State-wide	10 mpg	19 mpg	22 mpg	25 mpg	99 mpg	23 mpg
Coast	10	19	21	24	55	22
Deschutes	12	19	2 1	24	55	22
East	13	17	21	24	67	21
Mid Wil. Valley	12	20	22	26	68	24
North Central	12	18	21	24	54	21
N. Wil. Valley	12	20	23	26	99	24
Southern Valley	12	19	22	25	72	23
South Central	10	17	20	24	55	24

According to Table 4.7, rural regions tended to have a higher percentage of fuel inefficient vehicles. For North Central, South Central, and Eastern Oregon, at least half of households tended to own vehicles with below average fuel economies, while a little more than a quarter owned above average fuel efficiency vehicles. In contrast, more regions with urban centers such as North Willamette Valley, Southern Valley, and Mid Willamette Valley had much lower rates of fuel inefficient vehicles. Nearly one third of households in those areas owned above average fuel efficiency vehicles. The exception to this trend is Deschutes. Despite including Bend MPO, only 22% of households owned above-average fuel efficient vehicles. This may be due to that urban area's remoteness–households living in Bend MPO may still have to navigate rough roads that favor fuel inefficient vehicle types such as pickup trucks. Bend may also exhibit certain intangible effects different from the MPOs in the Willamette

Table 4.7: Household weighted mpg ratings of households that drove, by region

	Percent of Households Below Average (<21 mpg)	Percent of Households at Average (21-24 mpg)	Percent of Households Above Average (>25 mpg)	Total Number of Households
Oregon State-wide	37%	32%	31%	15,402
Coast	46	29	25	1,276
Deschutes	44	34	22	1,044
East	52	27	21	1,026
Mid Wil. Valley	34	32	33	5,426
North Central	50	27	23	368
N. Wil. Valley	29	34	37	3,707
Southern Valley	38	32	30	2,098
South Central	53	27	20	457

Valley.

Following the calculation of household mpg ratings, household cost per mile of driving under the gas tax and under the proposed RUC fee was developed. Under the gas tax, the cost per mile of driving was simply the household reported gas price divided by the household mpg rating. Under a VMT fee, the household cost per mile of driving is the household reported gas price absent the $0.30 gas tax divided by the household mpg rating, plus the per mile fee of $0.015. The $0.015 per mile fee is considered revenue neutral as compared to the $0.30 per gallon gas tax, under ODOT's assumption that the state-wide average mpg is 20 mpg (Whitty 2013).

The OHAS questionnaire asked respondents to report household income, by choosing one of eight categories of income ranges or to decline to answer. The median incomes of each range were assigned to households. However, the upper category was $150,000 or more. According to the 2011-2013 ACS from the Census Bureau, the median income of Oregon households with $150,000 or more was $201,000. Therefore, this research assumes that the OHAS data reflects census data, and assigns the 931 Oregon households that belong to this income tier an income of $201,000.

Table 4.8: Mean Household Incomes by Region

	Mean	Declined to respond
Oregon State-wide	$69,410	1,172
Coast	$59,470	58
Deschutes	$77,780	61
East	$65,350	61
Mid Wil. Valley	$71,410	282
North Central	$64,220	14
N. Wil. Valley	$84,740	303
Southern Valley	$59,840	219
South Central	$56,920	15

Consistent with literature, average incomes for rural regions lag behind urban regions (Crandall and Weber 2005). North Willamette Valley and Deschutes have the highest mean incomes, perhaps reflecting both better job opportunities as well as wages reflecting higher costs of living in Portland and Bend, respectively. The lowest mean incomes are found in South Central Oregon.

North Willamette Valley, which includes the Portland metropolitan area, and the Mid Willamette Valley, which includes the MPOs of Albany, Bend, Corvallis, Eugene/Springfield, and Salem/Keizer, has the highest number of households reporting an income of less than $15,000. The 199 sub-$15,000 income households in the Mid Willamette Valley and the 103 sub-$15,000 income households in North Willamette Valley seem large when compared to other parts of the state. However, it comprises only 3.9% of all Mid Willamette Valley and just 3% of all North Willamette Val-

Table 4.9: Household Income Category Counts by Region

	$0 - $14,999	$15,000 - $24,999	$25,000 - $34,999	$35,000 - $49,999	$50,000 - $74,999	$75,000 - $99,999	$100,000 - $149,999	$150,000 or more
Statewide	850	1,615	1,604	2,366	3,787	2,903	2,038	931
Coast	95	163	137	202	292	180	107	42
Deschutes	44	53	78	110	254	193	136	85
Mid Wil. Val	199	451	485	780	1,266	966	718	279
North Central	18	44	40	45	91	68	35	13
N. Wil. Val	103	205	249	425	757	666	632	367
S. Val	132	253	220	311	433	303	165	62
South Central	32	0	59	61	107	66	36	11

ley households that reported an income. Comparatively, the 18 sub-$15,000 income households in North Central is representative of 5.1% of that region's income reporting households, while South Central's 132 lowest income households make up 6.7% of that region's total number of income reporting households. North Willamette Valley has the largest number of households that earn $150,000 or more, containing 39.4% of the state's wealthiest households.

Because of the limitations of the data, approximating daily income is easier to accomplish than annualizing household' VMTs. As the research is concerned with daily VMT, in order to keep units consistent, daily household income figures were calculated by dividing household incomes by 365, the number of days in a year.

In some ways, the OHAS is a richer dataset than the NHTS used in other transportation research: It includes every household's street address and a five tiered rural-urban scale based on population density; the NHTS uses a single dummy variable to distinguish between rural and urban location types based on the 2000 US Census designations. The five location types used in the OHAS are derived from the US Census' data on census block population densities. Location types are defined as:

1. "Rural," greater than 2 miles to accumulate 2,500 people and greater than 15 miles to accumulate 50,000 people.
2. "Isolated City," less than 2 miles to accumulate 2,500 people but greater than 15 miles to accumulate 50,000 people.
3. "Rural Near Major Center," greater than 1 mile to accumulate 2,500 people but less than 15 miles to accumulate 50,000 people.
4. "City Near Major Center," less than 1 mile to accumulate 2,500 people and less than 15 miles to accumulate 50,000 people.
5. "MPO," less than 1 mile to accumulate 2,500 people and less than 5 miles to accumulate 50,000 people.

Table 4.10 compares three possible household classification systems, the OHAS location types, the NHTS urban/rural method, and a MPO/non-MPO split. To stay consistent with the most recent NHTS dataset, the 2000 US Census urban/rural definitions were applied to OHAS households. Thus, the differences between the OHAS location types and the NHTS classification schemes may be partially due to the NHTS definitions relying on older population density data while the OHAS used 2010 data to determine household location types. MPOs are those that were previously identified by ODOT. Using NHTS standards, 97% of OHAS "MPO" type and 96% of "city near major center" type households would be considered "urban." Additionally, 83% of "isolated cities" type households would also be classified as "urban" by the NHTS. 97% of "rural" households as defined by the OHAS coincide with the NHTS definition of a "rural" household, while 83% of "rural near major center" type households would also be classified as "rural" by the NHTS. "Isolated city," "city near major center," and "MPO" type households can be grouped together to form an OHAS equivalence of NHTS urban households. Likewise, "rural" and "rural near major center" type households could be grouped to form an NHTS rural equivalent. However, this research opts instead to directly use the NHTS definition of urban and rural.

Table 4.10: State-wide number of households in geospatial classification schemes

Location Types	OHAS	Urban (NHTS)	Rural (NHTS)	MPO (ODOT)	Non-MPO (ODOT)
Rural	1,574	51	1,523	8	1,566
Isolated Cities	1,636	1,365	271	0	1,636
Rural near M. C.	2,379	406	1,973	548	1,831
City near M. C.	2,004	1,895	109	530	1,474
Major Center	7,809	7,577	232	7,789	20
Total HHs	15,402	11,294	4,108	8,875	6,527

The OHAS's Oregon-centric focus results in a far greater sample size which allows for a more accurate depiction of the variation of different kinds of households across the state. However, because the OHAS is not primarily a transportation research dataset, it does not include certain variables that previous research has relied on, such as annual per vehicle VMT and annual gallons of gas consumed. Additionally, the two datasets do not share the same set of household attribute variables. The NHTS records the age, gender and education level of the household head, household income, as well as the number of children in a household; the OHAS categorizes the age of the household head, categorizes household incomes, and records the number of students in a household.

From the data, it appears that rural areas lag behind urban areas in household income. The data also shows that households in regions without urban centers tend to have a greater percentage of vehicles below average fuel economy, which may help offset a mileage-based road usage charge. The next section will seek to evaluate both of these factors in the face of a RUC by presenting results from the static model, in which household behaviors are assumed unchanging.

Chapter 5: Results

The following section first presents results from the static model by geographic delineation, starting from a state-wide overview, followed by an inter-regional examination, and finally consideration of individual MPOs. The second part of the results focuses on VMT regression results that may provide insights into differences in driving behavior in different locations. These findings can help policymakers better formulate RUC policies to mitigate perceived negative impacts on different locations. Regression results are similarly organized by geographic scale, starting with the state-wide level, and ending at the MPO level.

5.1 Static Model Results

The results of the static model using household weighted mpg values for the state of Oregon are as shown in the following table. State-wide, all households regardless of income level will pay at least \$0.04 more per day under a road usage charge of 1.5 cents per mile than the current fuel tax of 30 cents per gallon[1]. Households earning \$50,000-\$149,999 can expect to pay more than the lower income households. Overall, households earning more than \$150,000 are seen to pay as much as, or less

[1] The 1.5 cents per mile value was calculated as being a revenue neutral fee using the assumption that the average vehicle fuel economy in Oregon is 20 mpg. With the current fuel tax of \$0.30 per gallon, the mileage based fee equivalent is \$0.015 per mile. However, since the OHAS data shows that the average vehicle fuel economy is between 21-24 mpg, the 1.5 cents per mile rate will result in households on average paying more under the RUC.

than, the lower income households. A table displaying all of the static model results using arithmetic mean, rather than weighted average, calculations of household fuel efficiencies can be found in Appendix B.

Table 5.1 shows the average daily net change in household expenditures per income category state-wide as a percent of daily median income. Numbers in parentheses below the percentage figure are the change in monetary terms. The RUC will increase daily household expenditures across all household income levels. All households earning incomes higher than $24,999 experience a greater dollar increase in payments than lower income category households. However, this increase in monetary amount for higher income groups is a smaller percent of their income than for the lower income groups. When considering state-wide Oregon as a whole, for instance, the lowest income group spends an additional 0.19% of their income daily, or 4 cents more, for driving under a RUC system, compared to the highest income group which spend an additional 0.01% of their daily income, for the same additional 4 cents charge, with a mileage fee. Thus, the change from a fuel tax to the RUC will increase regressivity.

Overall, households that lie within an MPO's boundaries can expect to pay more on average than their non-MPO counterparts for every income category. When using the NHTS methodology for dividing households into urban and rural, the static model suggests that urban households will pay more than rural households within the same income bracket. Similar results are found when comparing the extremes of the location type categories. "MPO" type households, the most urban, pay more than "rural" type households, the most rural, within each income group. This suggests

Table 5.1: Average Daily Net Percent Change State-wide in Household Expenditures by Income Category

	$0 - $14,999	$15,000 - $24,999	$25,000 - $34,999	$35,000 - $49,999	$50,000 - $74,999	$75,000 - $99,999	$100,000 - $149,999	$150,000 or more
Oregon	0.19% ($0.04)	0.07% ($0.04)	0.06% ($0.05)	0.03% ($0.04)	0.03% ($0.05)	0.03% ($0.07)	0.02% ($0.06)	0.01% ($0.04)
MPO	0.19 (0.04)	0.09 (0.05)	0.06 (0.05)	0.04 (0.05)	0.04 (0.06)	0.04 (0.07)	0.02 (0.07)	0.01 (0.07)
Non-MPO	0.19 (0.04)	0.07 (0.04)	0.05 (0.04)	0.03 (0.04)	0.02 (0.04)	0.03 (0.06)	0.00 (0.04)	0.00 (- 0.02)
NHTS Urban	0.19 (0.04)	0.09 (0.05)	0.05 (0.04)	0.03 (0.04)	0.03 (0.05)	0.03 (0.07)	0.02 (0.07)	0.0 (0.06)
NHTS Rural	0.15 (0.03)	0.05 (0.03)	0.06 (0.05)	0.04 (0.05)	0.03 (0.05)	0.03 (0.06)	0.01 (0.05)	0.00 (0.00)
LT1 Rural	0.10 (0.02)	0.04 (0.02)	0.02 (0.02)	0.03 (0.04)	0.02 (0.03)	0.01 (0.03)	0.02 (0.07)	- 0.01 (- 0.05)
LT2 Isol. Cities	0.19 (0.04)	0.09 (0.05)	0.02 (0.02)	0.01 (0.01)	0.02 (0.03)	0.02 (0.05)	0.00 (- 0.01)	- 0.02 (- 0.09)
LT3 Rural M. C.	0.24 (0.05)	0.07 (0.04)	0.09 (0.07)	0.05 (0.06)	0.04 (0.07)	0.03 (0.08)	0.01 (0.05)	0.00 (0.02)
LT4 City M. C.	0.19 (0.04)	0.09 (0.05)	0.05 (0.04)	0.04 (0.05)	0.03 (0.05)	0.03 (0.06)	0.02 (0.07)	0.01 (0.03)
LT5 MPO	0.19 (0.04)	0.09 (0.05)	0.06 (0.05)	0.04 (0.05)	0.04 (0.06)	0.03 (0.07)	0.02 (0.07)	0.01 (0.07)

that the households located far from urban centers will pay more under a RUC system will actually pay less than D'Artagnan's (2013) findings suggest. However, because the relationship in net expenditure change between "isolated cities," "rural near major center," and "city near major center" households are not as clear, the D'Artagnan's results may still hold for certain situations.

While the state-wide results are useful for policy makers to see how households are impacted on a general level, regional effects in rural areas with small sample sizes may be masked by effects in large sample sizes concentrated around Portland Metro. The following table disaggregates the static model results from a state-wide level into the eight regional definitions specified by ODOT as relevant for this study (Coast, North Willamette Valley, Mid Willamette Valley, Southern Valley, North Central, Deschutes, South Central, and East). As before, the first value in each cell represents the daily change of switching from a fuel tax to a RUC as a percentage of daily median income, while the values in parentheses are changes in expenditures in monetary terms.

Table 5.2: Average Daily Net Percent Change in Regional Household Expenditures by Income Category

	$0 - $14,999	$15,000 - $24,999	$25,000 - $34,999	$35,000 - $49,999	$50,000 - $74,999	$75,000 - $99,999	$100,000 - $149,999	$150,000 or more
Coast	0.07% ($0.03)	0.07% ($0.04)	0.02% ($0.02)	- 0.02% (- $0.02)	0.02% ($0.04)	0.00% ($0.01)	0.00% ($0.00)	- 0.02% (- $0.09)
N. Wil. Valley	0.24 (0.05)	0.09 (0.05)	0.07 (0.06)	0.05 (0.06)	0.04 (0.06)	0.04 (0.09)	0.03 (0.09)	0.02 (0.09)
Mid Wil. Valley	0.19 (0.03)	0.09 (0.06)	0.07 (0.05)	0.04 (0.05)	0.04 (0.05)	0.03 (0.08)	0.02 (0.06)	0.01 (0.02)
Southern Valley	0.10 (0.02)	0.09 (0.05)	0.06 (0.05)	0.04 (0.05)	0.02 (0.04)	0.03 (0.07)	0.02 (0.06)	0.01 (0.05)
North Central	0.49 (0.10)	0.02 (0.01)	0.00 (0.00)	0.04 (0.05)	0.00 (0.00)	0.02 (0.05)	0.01 (0.04)	0.00 (- 0.02)
Deschutes	0.05 (0.01)	0.04 (0.02)	0.06 (0.05)	0.02 (0.02)	0.02 (0.03)	0.01 (0.03)	0.01 (0.03)	0.00 (0.02)
South Central	0.24 (0.05)	0.04 (0.02)	0.01 (0.01)	0.03 (0.03)	- 0.02 (- 0.03)	0.01 (0.02)	- 0.01 (- 0.04)	- 0.03 (- 0.18)
East	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.03 (0.03)	0.01 (0.01)	0.01 (0.02)	0.01 (0.03)	- 0.02 (- 0.13)

These results show that the North Willamette Valley, the Mid Willamette Valley, and Southern Valley largely follow state-wide trends in changes in household expenditures under a RUC; Deschutes to a lesser extent does as well. Static results for North Central, South Central, and to some degree the Coast, however, seem to indicate that a RUC will have a higher impact on low income households than high income households. Interestingly, the households earning $150,000 or more in these less urbanized regions will pay less under a RUC than the current fuel tax. As the static model does not allow for households to change their behaviors, these savings may be attributed to a more widespread use of fuel inefficient vehicles amongst wealthy households. This may manifest itself in increased ownership and use rates of SUVs or four wheel drive vehicles, relative to households in other income groups in their respective regions.

McMullen and Eckstein (2013) found that the determinants of VMT demand differed across cities in the United States as each city had a different industrial mix and other varying characteristics. Within Oregon, there may be different determinants of VMT demand between the nine MPOs that effect household VMT. For example, public transit facilities such as light rail may motivate households in Portland to drive less than households in Albany, ceteris paribus. While the static model is unable to determine the impact of such factors on household VMT demand, it can approximately describe the outcome in terms of whether a household pays more or less under a RUC system than a fuel tax as a result of the factors that influence driving. Table 5.3 shows the average daily net percent change in household expenditures for each MPO by income category using weighted household fuel efficiency measures. While at first glance, it appears that wealthy households in Walla Walla Valley would pay much more under a RUC scheme than they do currently, it is important to remember that only Walla Walla Valley MPO only contains 49 driving households. Because of the small sample size, it is difficult to draw any conclusions from either the static model or a dynamic model for this MPO.

Table 5.3: Average Daily Net Percent Change in MPO Household Expenditures by Income Category

	\$0 - \$14,999	\$15,000 - \$24,999	\$25,000 - \$34,999	\$35,000 - \$49,999	\$50,000 - \$74,999	\$75,000 - \$99,999	\$100,000 - \$149,999	\$150,000 or more
Portland	0.24% (\$0.05)	0.09% (\$0.05)	0.07% (\$0.06)	0.04% (\$0.05)	0.04% (\$0.06)	0.04% (\$0.09)	0.03% (\$0.09)	0.01% (\$0.08)
Salem/ Keizer	0.19 (0.04)	0.07 (0.04)	0.06 (0.05)	0.03 (0.04)	0.04 (0.06)	0.03 (0.07)	0.02 (0.06)	0.01 (0.06)
Albany	- 0.05 (- 0.01)	0.20 (0.11)	0.11 (0.09)	0.03 (0.04)	0.04 (0.06)	0.04 (0.09)	0.01 (0.04)	0.01 (0.05)
Corvallis	-0.05 (- 0.01)	0.05 (0.03)	0.07 (0.06)	0.06 (0.07)	0.02 (0.03)	0.04 (0.10)	0.03 (0.09)	0.01 (0.04)
Eugene/ Spring-field	0.19 (0.04)	0.07 (0.04)	0.05 (0.04)	0.04 (0.05)	0.04 (0.06)	0.02 (0.05)	0.02 (0.08)	0.01 (0.08)
Middle Rogue	0.05 (0.01)	0.11 (0.06)	- 0.04 (- 0.03)	0.03 (0.03)	0.01 (0.01)	0.06 (0.15)	0.02 (0.08)	0.01 (0.03)
Medford	0.15 (0.03)	0.07 (0.04)	0.06 (0.05)	0.04 (0.05)	0.04 (0.06)	0.02 (0.05)	0.01 (0.05)	0.01 (0.03)
Bend	0.15 (0.03)	0.05 (0.03)	0.07 (0.06)	0.02 (0.02)	0.02 (0.04)	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)
Walla Walla Valley	0.00 (0.00)	0.02 (0.01)	0.07 (0.06)	- 0.01 (- 0.01)	0.02 (0.04)	0.04 (0.09)	0.01 (0.03)	0.09 (0.51)

5.2 VMT Regression Results

5.2.1 State-wide VMT Determinants

As stated elsewhere, the restriction that households cannot change their driving behaviors or vehicle choices in the face of a transition to a RUC system is unrealistic beyond the very short term. The research by Kastrouni et al. (2012) and McMullen and Eckstein (2010) suggests that driving behavior may differ considerably from region to region. In some regions, drivers may be more sensitive to changes in the price of fuel or to demographic factors; this may, in the long run, contribute to regional differences in the impact of VMT reduction policies or the impact of changing from a fuel tax to a RUC. Accordingly, we now examine in detail the determinants of driving, as defined by household VMT using the OLS regression model.

The following table shows OLS regression results for households' VMT demand, dependent on household daily income, price per mile traveled, household fleet characteristics, and household demographic attributes. Price per mile traveled as calculated only captures the price per gallon of gas a household spends. The true cost of traveling by a motor vehicle includes factors considered externalities such as environmental degradation in terms of greenhouse gas emissions in the case non-electric vehicles, noise pollution, and contribution to congested road conditions during peak hours, as well as wear-and-tear on personal vehicles. The additional data required to include these additional costs are not included in the OHAS dataset; therefore, the price per mile traveled is limited to solely the amount a household spends on fuel.

From the static analysis, it was seen that using a MPO/non-MPO split as defined by households' locations within a state government defined metropolitan planning organization's boundaries and an urban/rural split as defined by the NHTS yield similar results in both in terms of comparisons between the different types of households within the same income category, as well as the magnitudes of change in household expenditures. Thus, for the purposes of estimating household VMT demand on a state-wide basis, the urban/rural split is used.

Table 5.4 shows the results from five regressions. Standard errors can be found in parentheses under immediately under their respective variable coefficient. Each column in the table represents a particular model specification; a short description of each specification follows.

(1.) This is a baseline regression in which no attempts were made to control for households' geospatial characteristics. (2.) A dummy variable is included to indicate whether or not a household lay within an MPO boundary. Since including dummy variables for all regions would result in perfect multicollinearity (and a singular matrix), standard practice is followed by omitting one dummy variable to make OLS estimation possible. In the case, the Portland MPO dummy is omitted. Thus, the resulting MPO dummy variable estimates reflect household VMT demand in those MPOs relative to household VMT behavior in the Portland MPO. (3.) This regression controls for households belonging to one of the eight possible regions by including dummy variables for seven of the eight regions (the Coast is omitted to prevent perfect multicollinearity as described above) Thus the reported regional dummy parameter estimates indicate household VMT behavior in each region relative to household VMT behavior in the Coastal Region. (4.) Households' proximity to areas of high population density is reflected in the five locational categories. Once again, one location type (rural) has been omitted; thus, resulting VMT demand for each location type is interpreted as relative to the rural location. (5.) While regressions (2.), (3.), and (4.) only control for each geospatial factor independently, this final regression controls for households belonging to one of the nine MPOs, eight regions, and five location types simultaneously. Like the previous model specifications, the Coast Region, Portland MPO, and rural location types were omitted.

	Dependent variable:				
	ln_HHVMT				
	Baseline	MPOs	Regions	Loc. Type	All loc. factors
ln_ppm.gas.w	−0.114***	−0.173***	−0.185***	−0.126***	−0.153***
	(0.031)	(0.036)	(0.035)	(0.032)	(0.037)
ln_dayINC	0.172***	0.163***	0.151***	0.167***	0.159***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
HHWRK	0.164***	0.161***	0.160***	0.167***	0.169***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
HHSTU	0.061***	0.061***	0.064***	0.065***	0.068***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
ln_HHVEH	0.456***	0.466***	0.485***	0.448***	0.459***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
ln_HHSIZ	0.186***	0.184***	0.184***	0.187***	0.180***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
SUBhyb	−0.132***	−0.152***	−0.170***	−0.138***	−0.155***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
SUBveh	0.011	0.028	0.031	0.011	0.021
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Urban (NHTS)	−0.483***	−0.508***	−0.543***	−0.184***	−0.162***
	(0.020)	(0.023)	(0.021)	(0.034)	(0.035)
Salem/ Keizer		−0.092***			−0.052
		(0.031)			(0.054)
Albany		0.038			0.068
		(0.067)			(0.082)
Corvallis		−0.208***			−0.214***
		(0.060)			(0.074)
Eugene/ Springfield		−0.190***			−0.139**
		(0.033)			(0.054)
Middle Rogue		−0.046			−0.141*
		(0.065)			(0.075)
Medford		−0.148***			−0.138**
		(0.038)			(0.058)
Bend		−0.245***			−0.038
		(0.041)			(0.079)
Walla Walla		−0.376***			−0.064
		(0.135)			(0.154)
N. Wil. Valley			0.321***		0.427***
			(0.037)		(0.076)

Table 5.4: State-wide OLS Regressions for Household VMT Demand

	Baseline	MPOs	Regions	Loc. Type	All loc. factors
Mid Wil. Valley			0.202*** (0.033)		0.343*** (0.050)
S. Wil. Valley			0.218*** (0.038)		0.340*** (0.054)
North Central			0.223*** (0.062)		0.238*** (0.061)
Deschutes			0.059 (0.045)		0.187*** (0.069)
South Central			0.074 (0.057)		0.073 (0.062)
East			−0.188*** (0.044)		−0.182*** (0.045)
Isol. City				−0.614*** (0.046)	−0.564*** (0.047)
Rural near M. C.				−0.030 (0.035)	−0.243*** (0.044)
City near M. C.				−0.342*** (0.047)	−0.530*** (0.054)
MPO				−0.379*** (0.044)	−0.615*** (0.062)
Constant	1.781*** (0.094)	1.690*** (0.101)	1.591*** (0.102)	1.871*** (0.096)	1.761*** (0.106)
Observations	14,389	14,389	14,389	14,389	14,389
R^2	0.207	0.211	0.220	0.220	0.232
Adjusted R^2	0.207	0.210	0.219	0.219	0.231
Residual Std. Error	1.026 (df = 14379)	1.024 (df = 14370)	1.018 (df = 14372)	1.018 (df = 14375)	1.010 (df = 14359)
F Statistic	417.731*** (df = 9; 14379)	214.085*** (df = 18; 14370)	252.726***) (df = 16; 14372)	311.666*** (df = 13; 14375)	149.806*** (df = 29; 14359)

Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors are shown in parentheses under their respective estimated coefficient values.

Although the magnitudes of coefficients differ slightly across these five regressions, the sign of each coefficient is consistent with expectations. As a log-log regression is being used, the price elasticity of demand is the coefficient of the price per mile, which is shown to be relatively inelastic. With a range of -0.114 to -0.173, depending on whether or not and which geospatial attribute is being controlled for, these estimated price elasticities are consistent with short-run fuel price elasticities found in the literature (Litman, 2012). With the exception of the vehicle type substitution dummy, all non-geographic dummy variables are significant at the 99% confidence interval. The low adjusted-R^2's are consistent with other studies using cross-sectional data (Andrews, 2005).

VMT appears to be a normal good, as VMT demand decreases when the price per mile increases. The positive coefficient for the household income variable implies that wealthier households travel more on a daily basis. Consistent with previous literature, households with employed members drive more than those without (McMullen et al, 2010). Similarly, households with multiple vehicles tend to travel more miles than those with fewer vehicles, and large households with many members tend to travel more than smaller households with fewer members (Weatherford, 2011). Consistent with NHTS findings, urban households tend to drive less than rural ones (Santos et al., 2011).

However, contrary to Small and Dender's (2007) rebound effect study results which find households owning fuel efficient vehicles driving more than households owning fuel inefficient vehicles, ceteris paribus, the hybrid vehicle substitution dummy, which is given the value one if a household owns a hybrid or electric vehicle, had a negative coefficient, regardless of whether or not household geospatial factors were being controlled for. Depending on the model specifications, households owning hybrid or electric vehicles drove between 12% and 16% less than households using traditional combustion engine vehicles, ceteris paribus. This suggests that households who own hybrid or electric vehicles may also have an additional unobserved attribute that deters them from driving compared to households owning only traditional motor vehicles. For instance, hybrid/EV owning households may be more environmentally conscious, and thus have a lower preference for driving, ceteris paribus. Additionally, it suggests that RUC revenues may be less than expected, as hybrid and electric vehicle owners may not free-ride as much as departments of transportation believe.

The negative coefficients on the urban/rural dummy supports previous studies in showing that rural households do drive more than urban households in Oregon (D'Artagnan, 2013). Regression results show that depending on which additional geospatial factors are being controlled for, urban households drive between 15% (in the case of **(5)**) and 42% (in the case of **(3)**) less than their rural counterparts, ceteris paribus.

Statewide, households in all MPOs, except for those in Bend, Albany, and Walla Walla Valley[2], whose differences were not statistically significant, drove less than Portland MPO households, ranging from 9% (Salem/Keizer MPO) to 19% (Corvallis MPO).

Households in East drove 17% less than their counterparts in the Coastal Region. Ceteris paribus, differences in driving behavior between Coast and South Central households were not statistically significant. The Willamette Valley regions and

[2]49 households were surveyed in Walla Walla Valley MPO. This small sample size implies OLS results are not robust for making comparisons

North Central region households drove between 18% (Mid-Willamette Valley) and 27% (North Willamette Valley) more than the Coastal households.

Households with rural location types drove more than those in all other location types. VMT demand for rural households near major centers was not found to be statistically different from that of rural households. However, isolated city households—although classified as rural in the NHTS data set— drove 46% less than their rural counterparts across the state. Thus, we find that there exist differences in VMT driving behavior in different types of rural households. This is a distinction possible with the OHAS data set that was not obvious from the NHTS data.

The R^2 increases when households' region, MPO, and location type designations are evaluated simultaneously, indicating that in order to better understand VMT demand as a function of a household's location, one needs to consider multiple aspects of location, including the population density of surrounding areas, the physical geography of a particular place, and other local attributes. For instance, when controlling for all location factors (MPO, Region, and location type), households in Deschutes region were found to drive 21% more than Coast region households but this difference was not statistically significant when only the regional dummy variable was considered. Prior to including all geographic factors, household VMT demand in Bend and Salem/Keizer appeared to be significantly lower than that of Coastal households–a result which turns insignificant when all geographic factors (MPO, Region, and locations type) are included. Compared to rural households, households in all other locations drove at least 22 percent less.

5.2.2 VMT Determinants by Regions

In the regression analysis that follows, some regions are considered separately from the rest, while others are grouped together and compared. "Free-standing" regions include the Coast and the North Willamette Valley. Unique historical factors may have shaped modern household VMT demand patterns on the Oregon Coast. The North Willamette Valley is dominated by the Portland Metropolitan. The Mid Willamette Valley, Southern Valley, and Deschutes regions are compared with each other as well as against a state-wide specification. These three regions each contain at least one MPO, have several other smaller population centers and are serviced by major highways, Interstate 5 for the two valley regions and a combination of US Routes 20 and 97 for Deschutes. Likewise, South Central and East regions are grouped and compared with each other. Superficially, these two regions appear fairly similar. Both are sparsely populated and relatively distant from urban areas. With the exception of households in Klamath Falls and the I-84 corridor, both regions contain predominantly rural households engaged in agricultural activities. These groupings were intentionally selected to compare seemingly similar regions with each other. Overall, the adjusted- R^2's in the regional models explain less than 30$ of the variation. This is unsurprising as households consider additional factors when deciding to go on trips besides the price per mile of driving. For instance, the reasons behind taking a trip may be far more important than the cost of the trip; however, as this data was not in the dataset it could not be included in the model.

Coastal Oregon communities had a different history than elsewhere, which affects household travel decisions. Communities along the Oregon Coast are connected by

US Route 101, a two lane highway containing periodic rough patches, hairpin curves, and many bridges. Construction on the Oregon stretch of US 101 began in 1919; it was completed in 1936. In contrast, pioneer settlement of the Oregon Coast began in the early 19th century. Although stagecoach lines were introduced in the late 19th century, their departure schedules were tide-dependent. The lack of bridges prevented them from operating between every town. Construction of the fourteen bridges that would eventually connect the coastal communities along US 101 began in 1921 and ended in 1936. Additionally, these communities were cut off from interior Oregon by the Pacific Coast Range, which may have contributed to a history of self sufficiency within each community. A table containing the number of isolated city type households and their respective towns may be found in the appendix.

While these towns have not reached a population density high enough to be considered cities by ODOT, they provide many of the same amenities that a city provides for its residents. ODOT officials suggest that this may cause households living along the coast to be considered "isolated city" households but exhibit travel demand more similar to "MPO" households. An isolated city household as defined by the OHAS means that one can travel less than two miles to accumulate 2,500 people but must travel more than fifteen miles to accumulate 50,000 people, whereas for an MPO household one can travel less than a mile to accumulate 2,500 people and less than five miles to accumulate 50,000 people.

Table 5.5 shows regression results of household VMT demand in Oregon Coast and non-Coast communities, respectively. While the OHAS contains five possible location types, the Coast region lacks the densest location type category, MPO.

Table 5.5: Coast versus Non-Coast Household VMT Demand, excluding MPOs

	Dependent variable:	
	ln_HHVMT	
	Coast	Non-Coast
ln_ppm.gas.w	−0.171	−0.265***
	(0.148)	(0.053)
ln_dayINC	0.160***	0.205***
	(0.053)	(0.022)
HHWRK	0.050	0.152***
	(0.048)	(0.019)
HHSTU	0.097*	0.047**
	(0.059)	(0.020)
ln_HHVEH	0.522***	0.392***
	(0.098)	(0.037)
ln_HHSIZ	0.339***	0.273***
	(0.118)	(0.046)
SUBhyb	−0.271**	−0.070
	(0.135)	(0.050)
Isol. City	−0.643***	−0.816***
	(0.075)	(0.050)
Rural near M. C.	0.173	−0.118***
	(0.292)	(0.041)
City near M. C.	0.048	−0.580***
	(0.724)	(0.043)
Constant	1.662***	1.451***
	(0.404)	(0.159)
Observations	1,218	5,916
R^2	0.191	0.221
Adjusted R^2	0.184	0.220
Residual Std. Error	1.243 (df = 1207)	1.076 (df = 5905)
F Statistic	28.478*** (df = 10; 1207)	167.798*** (df = 10; 5905)
Note:		*p<0.1; **p<0.05; ***p<0.01

Thus, when considering the rest of the state of Oregon, households that are labeled as MPO are intentionally omitted, in order to be able to compare the results between Coast and non-Coast household VMT demand functions. In both regressions, the location type defined as rural is omitted to prevent multicollinearity. Thus, the location type coefficients listed are relative to rural location type households.

With the exception of the hybrid vehicle substitution dummy, the results for non-Coast households generally follow the state-wide results discussed previously. This is likely due to the omitted MPO households owning the majority of these vehicle types in the rest of the state. Compared to non-Coastal Oregon, the price per mile of traveling and the number of household workers, while attached to coefficients pointing in expected directions, do not significantly affect a coastal household's VMT demand. Of the location type dummies, only the isolated city dummy is significant and negative. The negative coefficient for this dummy variable is not unique to the Coast region. Unlike Coast however, in all other regions, additional location type dummies are found to be statistically significant as well.

Though insignificant, the coefficients for the other two location type variables in the estimation of Coast household VMT demand are positive. The -0.643 coefficient for isolated city type households means that those households drive 47% less than rural households as well as every other location type households in Coast, ceteris paribus. This result implies that there may be some validity to ODOT's claims that historical transportation factors can still be felt today amongst households in Coastal Oregon in the form of VMT demand schedules. However, an alternative explanation may be found in regional demographics and household life cycles. Considered a desirable place to live due to its natural amenities, the Coastal region is becoming a popular retirement destination. As elderly households tend to drive less than younger households, the reduction in VMT may be due to the age of residents in the region rather than a historical legacy. However, since the OHAS does not include data on the ages of household members, this hypothesis is untestable.

Table 5.6 compares household VMT determinants for those residing in the North Willamette Valley against the rest of Oregon. Unlike Coast, which lacks any MPOs, North Willamette Valley contains the cities of Portland, Gresham, Hillsboro, Tigard, and Beaverton, collectively referred to as Portland Metro. Although North Willamette Valley does include non-MPO households, one suspects their relative proximity to Portland Metro will cause those households to behave quite differently from otherwise similar households elsewhere in the state. Additionally, an abundance of public transit facilities or alternative transportation modes and other non-observable factors may mean North Willamette Valley household travel behaviors in general are quite different compared to the rest of the state.

Results from Table 5.6 indicate that the price per mile, household size, and household location types is less statistically significant for households in the North Willamette Valley than elsewhere in the state. Additionally, the size of the coefficient is a lot smaller, which indicates that there is less sensitivity to changes in the price of driving. This may indicate that despite being an urbanized area containing Portland Metro, which has public transit and biking facilities, the reach of these alternative transportation modes may not extend beyond metropolitan limits. Thus, residents of North Willamette Valley that do not live within Portland MPO may

Table 5.6: North Willamette Valley and Rest of Oregon Household VMT Determinants

	Dependent variable:	
	ln_HHVMT	
	N. Wil. Valley	Rest of Oregon
ln_ppm.gas.w	−0.128*	−0.222***
	(0.070)	(0.038)
ln_dayINC	0.135***	0.168***
	(0.025)	(0.015)
HHWRK	0.199***	0.154***
	(0.024)	(0.014)
HHSTU	0.120***	0.049***
	(0.023)	(0.015)
ln_HHVEH	0.551***	0.459***
	(0.045)	(0.027)
ln_HHSIZ	−0.026	0.254***
	(0.053)	(0.033)
SUBhyb	−0.190***	−0.155***
	(0.059)	(0.036)
Isol.	1.150*	−0.765***
City	(0.619)	(0.038)
Rural	0.642*	−0.079**
near M. C.	(0.328)	(0.036)
City	0.179	−0.518***
near M. C.	(0.337)	(0.037)
MPO	0.124	−0.610***
	(0.324)	(0.033)
Constant	1.482***	1.632***
	(0.365)	(0.112)
Observations	3,404	10,985
R^2	0.217	0.224
Adjusted R^2	0.214	0.223
Residual Std. Error	0.913 (df = 3392)	1.046 (df = 10973)
F Statistic	85.293*** (df = 11; 3392)	288.326*** (df = 11; 10973)
Note:		*p<0.1; **p<0.05; ***p<0.01

be insensitive to changes in the price of driving, causing the coefficient to have a smaller than otherwise expected magnitude. The magnitude of effect that the presence of students in a household has on VMT demand is more than double in North Willamette Valley. This indicates that households with students may need to drive more than their counterparts in other parts of the state. North Willamette Valley, which includes Clackamas, Multnomah, and Washington counties, also includes the majority of colleges and universities in Oregon. As one possible explanation, off-campus college students may need to commute more often to attend classes than primary and secondary school students attending local schools do in other parts of the state. North Willamette Valley households' location types are only significant to the 90% confidence interval whereas in the rest of the state they are significant to the 99%. Both isolated city households and rural near major center households in North Willamette Valley travel quite a bit more than their rural counterparts, at 216% and 90% more, respectively. Isolated city households may be located in the exurbs of the Portland Metro area. Rural near major center type households may reside in the small towns surrounding the metropolitan. Depending on how far from city cores they reside, household members may have to commute further in order to reach work, school or shopping destinations. This in turn would increase daily household VMT demand. This may also partly explain why the coefficients for number of workers and number of students in North Willamette Valley households are greater than those variables for households in the rest of the state.

The first of the two inter-regional comparisons is between the Mid Willamette Valley, Southern Valley, and Deschutes regions. The Mid Willamette Valley contains the largest sample size amongst the regions, and includes several MPOs as well as rural areas. MPOs included in the Mid Willamette Valley are Salem/Keizer, Corvallis, Albany, and Eugene/Springfield. Directly south is Southern Valley, which contains Middle Rogue (Grants Pass) and Medford MPOs, as well as Roseburg. Interstate 5 runs north-south through both of these regions, and several additional local population centers lie along it. The Deschutes region includes Bend MPO, and Redmond. US Route 20 runs east-west, and US Route 97 runs roughly north-south, through the region. Table 5.7 contains the coefficients from estimating household VMT demand for Mid Willamette Valley, Southern Valley, and Deschutes.

While the sign of the coefficient of the price per mile is negative as one would expect, for the Mid Willamette Valley and Southern Valley it is not statistically significant. This means that households consider additional factors beyond price per mile of travel when deciding to go on trips. Additionally, the hybrid vehicle substitution dummy is not statistically significant in the Southern Valley. This is perhaps due to a shortage of number of households that own such vehicle types in the region. Most of the other variables in each region tend to follow state-wide trends.

In the multiple regression models, perfect multicollinearity between the location type dummies would result if all dummies were included. To prevent this, one dummy is omitted. Another way of explaining this is that in the case of perfect multicollinearity, the predictor matrix is singular and cannot be inverted, which means the OLS estimator does not exist. Of the five location type dummies, the dummy variable representing rural was omitted so that the resulting coefficients must be interpreted relative to rural areas.

Table 5.7: Valley and Deschutes Household VMT Determinants

	Dependent variable:		
	ln_HHVMT		
	Mid Wil. Val.	Southern Val.	Deschutes
ln_ppm.gas.w	−0.083	−0.098	−0.314**
	(0.060)	(0.080)	(0.126)
ln_dayINC	0.163***	0.128***	0.168***
	(0.022)	(0.033)	(0.048)
HHWRK	0.211***	0.144***	0.186***
	(0.020)	(0.030)	(0.044)
HHSTU	0.063***	0.063*	0.111**
	(0.020)	(0.036)	(0.049)
ln_HHVEH	0.498***	0.406***	0.489***
	(0.039)	(0.060)	(0.090)
ln_HHSIZ	0.133***	0.305***	0.199*
	(0.046)	(0.071)	(0.113)
SUBhyb	−0.115**	−0.065	−0.220**
	(0.050)	(0.078)	(0.110)
Isol. City	−0.784***	−0.278	0.126
	(0.129)	(0.182)	(0.227)
Rural	−0.453***	−0.270***	−0.033
near M. C.	(0.082)	(0.079)	(0.173)
Urban	−0.796***	−0.776***	−0.347*
near M. C.	(0.084)	(0.080)	(0.178)
MPO	−0.989***	−0.933***	−0.449**
	(0.078)	(0.086)	(0.174)
Constant	2.318***	2.331***	1.222***
	(0.179)	(0.242)	(0.394)
Observations	5,144	1,879	983
R^2	0.241	0.284	0.225
Adjusted R^2	0.240	0.279	0.216
Residual Std. Error	0.991	0.954	0.974
	(df = 5132)	(df = 1867)	(df = 971)
F Statistic	148.277***	67.216***	25.656***
	(df = 11; 5132)	(df = 11; 1867)	(df = 11; 971)
Note:			*p<0.1; **p<0.05; ***p<0.01

Of the three regions, the isolated city dummy is statistically significant only for Mid Willamette Valley households. In general, the Mid Willamette Valley is more densely populated than the other two regions, and contains more cities. Thus, households living in suburbs or exurbs may be captured by this indicator; their relative proximities to urban areas may mean they need to travel a much smaller distance than rural households. Using similar logic, the coefficients for both "rural near major center" and "city near major center" dummies are similarly more significant for the Mid Willamette Valley households than for Deschutes households. The magnitudes of coefficients for the location type dummies in Southern Valley are larger than those of other regions and the state. This may also be due to the presence of multiple cities and relatively larger population densities.

As the signs for most location type dummy variables are negative, one can infer that rural households in these regions drive more than any other household type. This finding supports information from opinion poll surveys (D'Artagnan, 2013). In the Mid Willamette Valley, households within MPO boundaries drive 62% less than rural households. In Southern Valley, Deschutes, and Oregon as a whole, households belonging to MPOs drive 61%, 36%, and 42% less, respectively.

The second inter-regional comparison is between the regions East and South Central. Both regions lie east of the Cascades, and are predominantly rural. Only East contains an MPO, Walla Walla Valley. As mentioned previously a lack of sample size means only inconclusive inferences can be drawn for Walla Walla Valley MPO. Despite being considered rural overall, these regions do contain several localized population centers: Klamath Falls in South Central, Pendleton, La Grande, Baker

City and Ontario along the I-84 corridor in East.

Due to the I-84 corridor, East region contains 113 "city near major center" type households. South Central also contains 217 "city near major center" type households, due to the presence of the large town of Klamath Falls. While North Central is also a rural region, it does not contain any "city near major center" type households, and is thus not included in this analysis. Its corresponding regression estimation can be found in the appendix. Both East and South Central regions lacked the population densities required for households to qualify as "MPO" type households. To stay consistent, MPO households were omitted from the state-wide regression estimation. Additionally, to avoid double counting, households that were in either South Central or East regions were omitted from consideration in the state-wide regression.

Unlike the state-wide results, price per mile, number of workers, number of students, and the hybrid vehicle substitution dummy are all statistically insignificant for South Central. The price per mile, number of household students, and households that are rural near major center are statistically insignificant for households in the East region. Although the effects of having an additional vehicle is lower in South Central than elsewhere, the effect an additional household member has on VMT demand is more than double the corresponding state-wide effect. Isolated city households in South Central are shown to drive 77% less than rural households; isolated city households in East drive 47% less than their rural counterparts.

The isolated city effect is larger than "city near major center" effects. Households of this type tend to reside in the large towns of their respective regions. In South Central, households who lived in towns drove just 61% less than rural households;

Table 5.8: Rural Regions Household VMT Determinants, excluding MPOs

	Dependent variable:		
	ln_HHVMT		
	South Central	East	Rest of Oregon (excluding MPOs)
ln_ppm.gas.w	−0.011	−0.263	−0.211***
	(0.228)	(0.174)	(0.055)
ln_dayINC	0.196**	0.280***	0.172***
	(0.078)	(0.060)	(0.022)
HHWRK	−0.034	0.183***	0.157***
	(0.067)	(0.053)	(0.019)
HHSTU	−0.051	0.017	0.085***
	(0.080)	(0.048)	(0.022)
ln_HHVEH	0.258**	0.421***	0.458***
	(0.129)	(0.097)	(0.038)
ln_HHSIZ	0.651***	0.263**	0.252***
	(0.166)	(0.122)	(0.048)
SUBhyb	0.195	−0.362**	−0.088*
	(0.211)	(0.141)	(0.051)
Isol.	−1.465***	−0.636***	−0.736***
City	(0.190)	(0.085)	(0.048)
Rural	−0.483***	0.031	−0.120***
Near M. C.	(0.166)	(0.170)	(0.042)
City	−0.939***	−0.583***	−0.538***
Near M. C.	(0.137)	(0.132)	(0.044)
Constant	2.254***	0.712	1.685***
	(0.624)	(0.459)	(0.162)
Observations	442	965	5,727
R^2	0.267	0.216	0.228
Adjusted R^2	0.250	0.208	0.227
Residual Std. Error	1.076 (df = 431)	1.169 (df = 954)	1.089 (df = 5716)
F Statistic	15.690*** (df = 10; 431)	26.262*** (df = 10; 954)	168.844*** (df = 10; 5716)
Note:			*p<0.1; **p<0.05; ***p<0.01

in East, households living in town drove 44% less than rural households. One explanation of the difference in driving habits between isolated city and town residents could be the presence, or lack thereof, of transportation infrastructure. Towns tend to lie along major arterial roads such as US and state highways. Isolated cities in rural regions tend to consist of large communities that are a further distance away from major roadways. Thus, it may be easier for households living in towns to travel than their more remote neighbors in isolated cities. These results indicate that even within predominantly rural regions of the state, there may be large variations between household location types. Overall, households in East seem to behave similar to other Oregon households of the same location types, in both significance levels and magnitudes of VMT determinants.

One of the limitations of comparing regions to each other is that the regional comparison level is too crude to distinguish between factor effects such as the presence of an accessible public transit network in a particular urban area, which may influence household VMT demand. The next subsection will compare household VMT determinants between a select few MPOs.

5.2.3 VMT Determinants by MPOs

Similar to the Regions subsection, not all MPO regressions are discussed in depth. Additional MPO regressions may be found in Appendix B. Due to the small number of households sampled, Walla Walla Valley is omitted entirely. These MPOs were chosen as they each include populations larger than 50,000 people. Additionally, they all lack rural and isolated city type households. MPO type households that were located in areas in which one could travel less than 1 mile before accumulating 2,500 people and less than 5 miles to accumulate 50,000 people were omitted because of multicollinearity. The MPO subsections is arranged as follows. First, results for Portland MPO are discussed. Afterwards is a comparison between Albany and Corvallis MPOs. As the sample size for Portland MPO is several times larger than that of Albany and Corvallis, no direct comparisons between the first and the latter two MPOs are made. Furthermore, because Albany and Corvallis MPOs only have a couple hundred observations, the OLS can only provide preliminary results. A larger dataset would provide a better estimate of the relative importance of VMT determinants in these two cities.

The coefficients for Portland MPO regressors behave as expected. Price per mile is only weakly significant, but has the expected direction. Household income, number of household workers and students, the number of household vehicles, and the hybrid vehicle substitution dummy are all statistically significant and point in expected directions. Household size is found to not play a factor in Portland MPO households. Contrary to state-wide regression results, the City near Major Center dummy is negative but not statistically significant. The Rural Near Major Center dummy is found to be statistically significant for Portland MPO. Its positive sign means that households of this type travel 50% more than MPO type households. A possible explanation for this is that MPO type households are those that are found in a city, whereas the City near Major Center type households may live on city outskirts or suburbia and therefore members must commute into the city in order to access

Table 5.9: Household VMT Demand in Select MPOs

	Dependent variable:		
	ln_HHVMT		
	Portland	Albany	Corvallis
ln_ppm.gas.w	−0.129*	−0.718**	0.026
	(0.073)	(0.331)	(0.250)
ln_dayINC	0.126***	0.267**	0.161*
	(0.026)	(0.112)	(0.097)
HHWRK	0.186***	0.128	0.109
	(0.025)	(0.102)	(0.084)
HHSTU	0.108***	0.123	−0.054
	(0.024)	(0.110)	(0.095)
ln_HHVEH	0.561***	0.608***	0.619***
	(0.047)	(0.203)	(0.160)
ln_HHSIZ	0.008	0.168	0.342*
	(0.055)	(0.251)	(0.206)
SUBhyb	−0.196***	0.170	−0.246
	(0.062)	(0.294)	(0.216)
Rural	0.408***	0.816***	0.449***
near M. C.	(0.135)	(0.246)	(0.164)
City	−0.021	0.626*	−0.018
near M. C.	(0.151)	(0.377)	(0.400)
Constant	1.645***	−0.458	1.447**
	(0.184)	(0.898)	(0.725)
Observations	3,095	211	280
R^2	0.188	0.270	0.219
Adjusted R^2	0.186	0.238	0.193
Residual Std. Error	0.910 (df = 3085)	1.037 (df = 201)	0.960 (df = 270)
F Statistic	79.401*** (df = 9; 3085)	8.278*** (df = 9; 201)	8.424*** (df = 9; 270)

Note: *p<0.1; **p<0.05; ***p<0.01

goods and services.

Albany and Corvallis MPOs are located eleven miles apart. Corvallis contains more than 54,000 residents while Albany has over 51,000. According to the 2013 American Community Survey nearly half of the total employment in Corvallis can be found in the educational services and health care and social assistance sector. Other major industry sectors in Corvallis include the hospitality sector and professional, scientific and management services. Due to it's improved access to rail and proximity to Interstate 5 compared to Corvallis, Albany is more of a manufacturing and agricultural hub. Although the educational services and health care and social assistance sector employs the most people in Albany, it provides just half the number of jobs the sector employs in Corvallis. Other major industry sectors include retail and manufacturing. 94.5% of residents in Corvallis have at least a high school diploma, compared to just 89% of Albany residents. The median age in Corvallis is 26, whereas the median age in Albany is 35. The differences in industry mix, education levels, and age of residents could affect preferences towards driving. Additionally, through time, these differences may lead to different cultural attitudes which affect how households within each MPO make travel decisions.

According to the regression results, households in Albany are much more sensitive to changes in the price per mile of travel than their counterparts in Corvallis. Based on the significance level, it would seem that Corvallis households do not make travel decisions based on traveling prices at all. The income elasticity of VMT demand in Albany is almost twice that of Corvallis, and more statistically significant. In both Corvallis and Albany MPOs, the impact the number of household workers and students have on household VMT demand is statistically insignificant, contrary to Mid Willamette Valley findings. An additional household vehicle would increase household VMT demand by roughly the same amount across both MPOs. The marginal effect of increasing a household's size by one member is statistically insignificant for households in Albany, and only significant to the 90% confidence interval for households in Corvallis.

While the hybrid vehicle substitution dummy variables for both MPOs are statistically insignificant, it is interesting to note that they have opposite signs. This opens up the possibility that household preferences and attitudes towards the environment are different between these two cities. It implies that households in Albany may be tempted to drive 18% more miles daily if they owned hybrid or electric vehicles, while households in Corvallis would curb their driving by 22% daily if they owned those vehicle types. Albany residents' behavior provides evidence that a rebound effect may occur, in which households owning more fuel efficient vehicles end up driving more. However, Corvallis residents' behaviors run contrary to the rebound effect theory. This implies that households in Corvallis may value environmental quality more than the low per mile costs of driving attributed to hybrid and electric vehicle ownership.

Rural near major center households are expected to travel 126% more than households that live within 1 mile of Albany's city center. In Corvallis, rural near major center type households are expected to travel only 57% more than households living within 1 mile of Corvallis's city center. The City near Major Center dummy is weakly significant for Albany MPO households. This variable's estimated coefficient suggests that households within 15 miles of Albany's city center will travel 87% more daily than households living within 1 mile of the city center. The same variable for Corvallis MPO implies a -2% difference in daily miles traveled; however, this variable is statistically insignificant for Corvallis MPO households. Overall these results indicate that while there may be some degree of truth to the conventional wisdom that Corvallis and Albany have fundamentally different characteristics, these differences do not appear to be statistically significant. The next section will address present key findings and recommendations for future work that can improve on this research.

Chapter 6: Conclusions

This study uses a new dataset to examine the impact on income groups and geographic regions of imposing a RUC in lieu of the traditional fuel tax to fund state highways. Using the newly available OHAS data set, this study provides impacts on a level of geographic specificity that was not possible using the previously available NHTS data set.

6.1 Key Findings

A static model is used to assess the impact of switching from the current 30 cents per gallon fuel tax to the 1.5 cents per mile RUC proposed by SB 810. It should be noted that this fee structure, combined with the fact that the average vehicle mpg in the OHAS data set is over 20 mpg, causes the average Oregon household to pay more under the RUC than the fuel tax. While all households will pay slightly more with a RUC, high income households on average state-wide will pay more than low income households. However since the increase in expenditures due to a RUC is a larger percentage of daily income for lower income households than for higher income households, the RUC is found to increase regressivity relative to the current fuel tax.

On average, rural households state-wide will be affected less than their urban counterparts. Upon disaggregating households into separate regions however, the distributional effects of RUC adoption are less clear. For instance, using the location types definitions of rural and MPO, rural households experience a smaller percent change in expenditures due to the RUC than their MPO counterparts for each income category. However, in the disaggregated regional analysis, the lowest income households in the predominantly rural regions of South Central and North Central Oregon have a larger daily net percent change in household expenditures due to the RUC than households in the mostly urban North Willamette Valley region.

Despite not providing annual vehicle VMT estimates that are necessary for a more complete analysis, the OHAS data was still helpful in revealing several key insights on determinants of household VMT. Regression results show that while urban/rural categorizations are an important first step in examining the geospatial aspects of households' VMT, they are not sufficient. Rather, increasingly disaggregated scales are necessary to better understand the role household location plays in VMT demand. A household's location within certain regions and MPOs is a statistically significant factor in determining household VMT demand. In general although rural households drive more than their relatively more urban counterparts, rural households in isolated cities drive less. This is particularly noticeable in the coastal region.

For instance, isolated rural communities in the Coast region drive less than other rural locations, and more like urban households in Portland in terms of VMT demand. Despite being two rural areas, East and South Central households have different determinants of VMT that would have been obscured if they had been grouped together. On the other hand, households in MPOs with different industry mixes, such as Albany and Corvallis, are shown to have mostly similar travel behaviors, although the possibility of slightly different attitudes towards travel may exist due to differing household preferences between the two cities.

A general finding of this research that should be given further study concerns the behavior of households with hybrid and electric vehicles. Previous studies by Weatherford (2011) and Paz (2013) dealing with vehicle substitutability using relative fuel efficiencies within a household's vehicle fleet find that households with the ability to switch between vehicles with varying mpg ratings tend to drive more than other households, a result consistent with research on the rebound effect (Small and Dender, 2007). However, the OHAS data indicates that Oregon households overall which own hybrid/EVs drive less. However, there are relatively few observations of hybrid/EVs in the dataset. Also, because the OHAS contains only daily household VMT rather than annual VMT, it is not possible to compare the results of this study with the prior NHTS-based studies or further explore the possible trade-offs between vehicles within a household. Therefore more data needs to be collected before research can conclusively state whether Oregon households with hybrid/EVs have different preferences. For instance, Oregon households that own hybrid/EVs could be more environmentally conscious than non-Oregon households with hybrid/EVs; this would help explain why hybrid/EV owning households' behaviors run counter to that which rebound effect research would suggest.

The OLS regression results from different regions indicate that the change in per mile price of driving caused by the switch to a RUC could have very different impacts in different areas as is evidenced by the differing magnitude and significance levels of the price coefficient in the VMT equations across locations. In some regions, the price elasticity of demand is small and insignificant. Larger magnitudinal values of this coefficient signify a smaller net impact than the static model results indicate. As the price elasticity of demand approaches zero, the static model's predictions become more accurate.

6.2 Future Work

The results found in this study show that it is important to examine households in locations that are defined in much more detail than those found in the NHTS dataset, as drivers in these locations respond differently to a change in the price per mile of driving. However, the data in the OHAS were not robust enough to support a dynamic impact analysis that would allow incorporation of long term tradeoffs between household vehicles and long term vehicle choice decisions. To enable research efforts that are comparable to those done using NHTS data, future OHAS surveys could include household attribute variables such the number of children in a household, and the age, education level, race, and gender of each member of the household. Information for each worker in a household, such as occupation, usual mode and time to work, the ability to work from home, and usual distance to work would allow future studies to better differentiate between VMT demand due to commuting to work and VMT demand due to leisure, as the former which may be more resistant to changes in the price per mile of driving. For each vehicle, odometer readings, annual miles driven reporting, and primary driver variables would allow for dynamic impact analyses similar to those done in previous RUC studies that used NHTS data. Trip data such as the time each trip started and ended, transit wait times if public transit was used, interstate highway use, tolls paid, and incidence of public transit use, motorcycle use, and biking trips, would assist research into household responses in terms of changing modal choice as a result of the adoption of a RUC. A multi-year dataset with these variables would be ideal, as the time series nature could provide further insights into how driving behaviors of households in each location have changed over time in the face of changing vehicle technologies.

In any case, this study shows that VMT behavior may differ considerably for different geographic locations within the state of Oregon. This suggests that the impact of a policy change such as the change from a fuel tax to a RUC may differ from region to region—even for regions usually treated as homogenous in past studies such as those classified as rural. To help ameliorate the potential negative impacts of such a policy in certain parts of the state, such regional differences should be explored in greater detail.

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APPENDICES

Appendix A: Static Model Results using Mean MPGs

Table A.1: Average Daily Net Percent Change State-wide in Household Expenditures by Income Category using Arithmetic Mean MPGs

	\$0 - \$14,999	\$15,000 - \$24,999	\$25,000 - \$34,999	\$35,000 - \$49,999	\$50,000 - \$74,999	\$75,000 - \$99,999	\$100,000 - \$149,999	\$150,000 or more
Oregon	0.19% (\$0.04)	0.07% (\$0.04)	0.06% (\$0.05)	0.04% (\$0.05)	0.03% (\$0.05)	0.03% (\$0.06)	0.02% (\$0.07)	0.01% (\$0.06)
MPO	0.18 (0.04)	0.07 (0.04)	0.05 (0.04)	0.04 (0.05)	0.02 (0.04)	0.02 (0.06)	0.02 (0.06)	0.00 (0.02)
Non-MPO	0.17 (0.03)	0.08 (0.04)	0.06 (0.05)	0.04 (0.05)	0.03 (0.06)	0.03 (0.07)	0.02 (0.08)	0.01 (0.07)
Urban (NHTS)	0.11 (0.02)	0.06 (0.03)	0.07 (0.05)	0.05 (0.05)	0.02 (0.04)	0.02 (0.06)	0.02 (0.06)	0.01 (0.04)
Rural (NHTS)	0.19 (0.04)	0.08 (0.04)	0.05 (0.04)	0.04 (0.05)	0.03 (0.06)	0.03 (0.07)	0.02 (0.07)	0.01 (0.07)
TYPE 1	0.09 (0.02)	0.07 (0.04)	0.06 (0.05)	0.05 (0.06)	0.01 (0.01)	0.00 (0.01)	0.02 (0.07)	- 0.00 (- 0.01)
TYPE 2	0.22 (0.04)	0.06 (0.03)	0.02 (0.02)	0.00 (0.01)	0.02 (0.03)	0.03 (0.06)	0.01 (0.02)	- 0.02 (- 0.08)
TYPE 3	0.17 (0.03)	0.05 (0.03)	0.06 (0.05)	0.05 (0.05)	0.03 (0.06)	0.03 (0.06)	0.02 (0.05)	0.01 (0.02)
TYPE 4	0.21 (0.04)	0.09 (0.05)	0.05 (0.04)	0.05 (0.06)	0.03 (0.06)	0.03 (0.07)	0.02 (0.07)	0.01 (0.06)
TYPE 5	0.17 (0.03)	0.08 (0.04)	0.06 (0.05)	0.04 (0.05)	0.03 (0.06)	0.03 (0.07)	0.02 (0.08)	0.01 (0.07)

Table A.2: Average Daily Net Percent Change in Regional Household Expenditures by Income Category using Arithmetic Mean MPGs

	$0 - $14,999	$15,000 - $24,999	$25,000 - $34,999	$35,000 - $49,999	$50,000 - $74,999	$75,000 - $99,999	$100,000 - $149,999	$150,000 or more
Coast	0.05% ($0.04)	0.05% ($0.03)	0.01% ($0.01)	- 0.02% ($0.02)	0.02% ($0.04)	0.02% ($0.05)	0.01% ($0.05)	- 0.01% (- $0.06)
N. Wil. Valley	0.24 (0.05)	0.09 (0.05)	0.07 (0.06)	0.05 (0.06)	0.04 (0.06)	0.04 (0.09)	0.03 (0.09)	0.02 (0.09)
Mid Wil. Valley	0.19 (0.04)	0.07 (0.04)	0.07 (0.06)	0.05 (0.06)	0.04 (0.07)	0.03 (0.07)	0.02 (0.07)	0.01 (0.07)
Southern Valley	0.10 (0.02)	0.09 (0.05)	0.06 (0.05)	0.04 (0.05)	0.02 (0.04)	0.03 (0.07)	0.02 (0.06)	0.01 (0.07)
North Central	0.39 (0.08)	0.04 (0.02)	- 0.01 (- 0.01)	0.02 (0.02)	0.01 (0.01)	0.02 (0.04)	0.02 (0.06)	- 0.01 (- 0.04)
Des-chutes	0.05 (0.01)	0.02 (0.01)	0.07 (0.06)	0.01 (0.01)	0.02 (0.03)	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)
South Central	0.24 (0.05)	0.07 (0.04)	0.01 (0.01)	0.03 (0.04)	- 0.01 (- 0.01)	0.00 (0.01)	- 0.02 (- 0.06)	- 0.02 (- 0.09)
East	0.00 (0.00)	0.00 (0.00)	0.02 (0.02)	0.04 (0.05)	0.01 (0.01)	0.00 (0.01)	0.01 (0.04)	- 0.02 (- 0.10)

Table A.3: Average Daily Net Percent Change in MPO Household Expenditures by Income Category using Arithmetic Mean MPGs

	$0 - $14,999	$15,000 - $24,999	$25,000 - $34,999	$35,000 - $49,999	$50,000 - $74,999	$75,000 - $99,999	$100,000 - $149,999	$150,000 or more
Portland	0.24% ($0.05)	0.09% ($0.05)	0.07% ($0.06)	0.05% ($0.06)	0.04% ($0.06)	0.04% ($0.09)	0.03% ($0.09)	0.02% ($0.09)
Salem/ Keizer	0.15 (0.03)	0.05 (0.03)	0.05 (0.04)	0.04 (0.05)	0.04 (0.06)	0.03 (0.06)	0.02 (0.07)	0.01 (0.07)
Albany	0.00 (0.00)	0.18 (0.10)	0.12 (0.10)	0.03 (0.04)	0.05 (0.08)	0.03 (0.08)	0.01 (0.02)	0.01 (0.07)
Corvallis	0.00 (0.00)	0.05 (0.03)	0.07 (0.06)	0.09 (0.10)	0.02 (0.03)	0.03 (0.08)	0.03 (0.10)	0.01 (0.04)
Eugene/ Spring-field	0.19 (0.04)	0.07 (0.04)	0.05 (0.04)	0.04 (0.05)	0.04 (0.07)	0.03 (0.06)	0.02 (0.08)	0.01 (0.07)
Middle Rogue	0.00 (0.04)	0.05 (0.04)	0.00 (0.04)	0.05 (0.05)	0.01 (0.07)	0.06 (0.06)	0.01 (0.08)	0.00 (0.07)
Medford	0.10 (0.02)	0.07 (0.04)	0.06 (0.05)	0.03 (0.04)	0.03 (0.05)	0.02 (0.05)	0.01 (0.05)	0.01 (0.07)
Bend	0.15 (0.03)	0.05 (0.03)	0.06 (0.05)	0.02 (0.02)	0.02 (0.04)	0.01 (0.02)	0.01 (0.03)	0.01 (0.03)
Walla Walla Valley	0.00 (0.00)	0.05 (0.03)	0.09 (0.07)	0.00 (0.00)	0.03 (0.05)	0.07 (0.17)	- 0.01 (- 0.03)	0.04 (0.21)

Appendix B: Additional OLS Regression Results

Table B.1: Additional Regressions of Regional Household VMT Determinants

	Dependent variable:
	ln_HHVMT
	North Central
ln_ppm.gas.w	−0.674***
	(0.251)
ln_dayINC	0.180**
	(0.086)
HHWRK	0.092
	(0.076)
HHSTU	0.014
	(0.084)
ln_HHVEH	0.290*
	(0.148)
ln_HHSIZ	0.573***
	(0.188)
SUBhyb	−0.025
	(0.208)
Isol. 2 Cities	−0.913***
	(0.123)
Rural near M. C.	0.024
	(0.260)
Constant	0.810
	(0.702)
Observations	354
R^2	0.314
Adjusted R^2	0.296
Residual Std. Error	1.059 (df = 344)
F Statistic	17.530*** (df = 9; 344)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table B.2: Additional MPO Regressions of Household VMT Determinants

	Dependent variable:				
	ln_HHVMT				
	Bend	Eugene/ Springfield	Medford	Middle Rogue	Salem/ Keizer
ln_ppm.gas.w	−0.241	0.083	0.001	−0.025	−0.074
	(0.156)	(0.101)	(0.130)	(0.336)	(0.112)
ln_dayINC	0.152***	0.097***	0.086*	0.144	0.166***
	(0.056)	(0.037)	(0.045)	(0.106)	(0.038)
HHWRK	0.205***	0.207***	0.154***	0.049	0.238***
	(0.052)	(0.035)	(0.044)	(0.107)	(0.037)
HHSTU	0.081	0.023	0.087*	0.001	0.068*
	(0.060)	(0.036)	(0.051)	(0.122)	(0.035)
ln_HHVEH	0.402***	0.490***	0.364***	0.589***	0.477***
	(0.108)	(0.067)	(0.093)	(0.205)	(0.071)
ln_HHSIZ	0.214	0.145*	0.139	0.346	0.113
	(0.140)	(0.084)	(0.108)	(0.214)	(0.077)
SUBhyb	−0.179	−0.209**	−0.070	0.189	−0.134
	(0.128)	(0.084)	(0.117)	(0.298)	(0.093)
Rural near M. C.			−0.523		
			(0.347)		
City near M. C.	0.350	−0.120	−0.909***	−0.221	
	(0.248)	(0.223)	(0.341)	(0.174)	
MPO	−0.202	−0.235	−1.128***	−0.228	−0.326***
	(0.127)	(0.168)	(0.341)	(0.173)	(0.106)
Constant	1.221***	2.254***	2.996***	1.796**	1.697***
	(0.424)	(0.321)	(0.480)	(0.887)	(0.319)
Observations	636	1,445	783	252	1,455
R^2	0.199	0.176	0.213	0.172	0.221
Adjusted R^2	0.188	0.171	0.203	0.141	0.217
Res. Std. Error	0.893 (df = 626)	0.878 (df = 1435)	0.880 (df = 772)	1.114 (df = 242)	0.943 (df = 1446)
F Statistic	17.329*** (df = 9; 626)	34.031*** (df = 9; 1435)	20.886*** (df = 10; 772)	5.581*** (df = 9; 242)	51.406***) (df = 8; 1446)

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix C: Isolated City Type Households' Locations by Region

Table C.1: Isolated City Households in Coast

Town Name	**No. Households**
Astoria	68
Bandon	17
Brookings	37
Clatsop	4
Coos	48
Coos Bay	94
Coquille	32
Curry	26
Florence	46
Gearhart	7
Lane	11
Lincoln	14
Lincoln City	43
Myrtle Point	14
Newport	53
North Bend	78
Reedsport	39
Seaside	21
Tillamook	40
Toledo	16
Waldport	11
Warrenton	18
Total	**737**

Table C.2: Isolated City Households in N. Central

Town Name	**No. Households**
Crook	13
Jefferson	20
Total	**33**

Table C.3: Isolated City Households in N. Wil. Valley

Town Name	**No. Households**
Clackamas	4

Table C.4: Isolated City Households in S. Central Region

Town Name	**No. Households**
Burns	24
Harney	2
Hines	2
Lakeview	20
Lake	5
Total	**53**

Table C.5: Isolated City Households in Deschutes

Town Name	**No. Households**
Deschutes	31
Sisters	4
Total	**35**

Table C.6: Isolated City Households in East

Town Name	**No. Households**
Baker City	78
Boardman	13
Hermiston	58
Irrigon	6
Island City	6
John day	19
La Grande	78
Malheur	4
Morrow	9
Pendleton	119
Umatilla	67
Union	10
Vale	13
Total	**480**

Table C.7: Isolated City Households in Mid. Wil. Valley

Town Name	**No. Households**
Cottage Grove	39
Lane	12
Linn	6
Oakridge	14
Sweet Home	23
Westfir	1
Total	**95**

Table C.8: Isolated City Households in N. Central

Town Name	**No. Households**
Crook	13
Jefferson	20
Madras	25
Prineville	42
The Dalles	77
Wasco	21
Total	**198**

Table C.9: Isolated City Households in S. Valley

Town Name	**No. Households**
Cave Junction	2
Douglas	16
Jackson	2
Josephine	6
Myrtle Creek	1
Oakland	2
Shady Cove	5
Total	**34**