OREGON DEPARTMENT OF TRANSPORTATION

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GREENSTEP & RSPM MODEL

VERSION 3.5

TECHNICAL DOCUMENTATION

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Introduction

The GreenSTEP and RSPM models are strategic planning models that assist state and metropolitan area planners with the evaluation of transportation and land use policy scenarios. These models consider a large number of factors which affect the performance of transportation systems and their effects on people and the environment. The GreenSTEP (Greenhouse gas Strategic Transportation Energy Planning) model was originally developed to assist the Oregon Department of Transportation (ODOT) with the analysis of alternative policies and other non-policy factors (e.g. gas prices) on greenhouse gas (GHG) emissions from the transportation sector. Subsequently, the scope of the model has evolved to enable the analysis of policy scenarios on a number of different aspects of transportation system performance and effects on people and their environment. The GreenSTEP model was also modified to create a strategic planning model for metropolitan areas, the RSPM (Regional Strategic Planning Model). GreenSTEP and RSPM are the same in most respects, but differ in how they model metropolitan areas. Whereas GreenSTEP treats a metropolitan area as a single entity, the RSPM divides the metropolitan area into divisions and districts and enables some policies to be represented differently at these smaller levels of geography. At this time, the models focus on light-duty vehicle travel. Travel by other modes is represented incompletely as is freight travel.

The GreenSTEP model was initially developed by the Oregon Department of Transportation (ODOT) Transportation Planning Analysis Unit (TPAU) as a modeling tool to assess the effects of a large variety of policies and other factors on transportation sector GHG emissions. This new model was developed because existing transportation, land use, and emissions models used in Oregon could not address the broad range of potential policies and other factors that affect transportation sector GHG emissions. The GreenSTEP model was developed to address the following factors, among others:

- Changes in population demographics (age structure);
- Changes in personal income;
- Relative amounts of development occurring in metropolitan, urban and rural areas;
- Metropolitan, other urban, and rural area densities;
- Urban form in metropolitan areas (proportion of population living in mixed use areas with a well interconnected street and walkway system);
- Amounts of metropolitan area transit service;
- Metropolitan freeway and arterial supplies;
- Auto and light truck proportions by year;
- Average vehicle fuel economy by vehicle type and year;
- Vehicle age distribution by vehicle type;

- Electric vehicles (EVs), plug-in hybrid electric vehicles (PHEVs)
- Light-weight vehicles such as bicycles, electric bicycles, electric scooters, etc.;
- Pricing – fuel, vehicle miles traveled (VMT), parking;
- Demand management – employer-based and individual marketing;
- Car-sharing;
- Effects of congestion on fuel economy;
- Effects of incident management on fuel economy;
- Vehicle operation and maintenance – eco-driving, low rolling resistance tires, speed limits;
- Carbon intensity of fuels, including the well to wheels emissions; and
- Carbon production from the electric power that is generated to run electric vehicles.

Model Design

In the beginning, it was anticipated that GreenSTEP would run at a county level. This design concept was motivated by the availability of long-range population projections by age at the county level and the need for the model to be sensitive to regional differences.

It was originally conceived as a "sketch-planning" model, starting with a base level forecast of VMT that reflects the population forecast. A series of factoring tables would then be used to adjust the VMT to reflect land use and transportation policies. The most uncertain and challenging portion of the design was to determine how to adjust VMT based on future increases in fuel cost or other costs.

A factoring approach can simplify the model development process, because it can draw from the research of others on the effects of policies or other actions on the quantity being forecasted (e.g. VMT, greenhouse gas emissions). The approach requires the review of multiple studies to identify general factors that describe the proportional effect that one variable (e.g. population density) has on another variable (e.g. VMT).

The factoring approach also has a number of limitations. First, since factors can vary significantly from one study to another due to differences in data and methods, judgment is required in order to choose the factor values to be used in the model. Inconsistencies between the studies used can make it difficult to choose which factors to use. Second, study differences in how the factors are defined and measured means that the factor values do not represent a mutually exclusive set of factors and their effects. Consequently there is a significant potential for the double-counting of effects when the factors are applied together. Accounting for the range of factors of interest and avoiding double counting is a significant challenge for a factor-based model.

GreenSTEP was redesigned to eliminate the need for most of the factoring elements and to replace them with disaggregate household-level models. This was done to take advantage of the available data, resolve technical difficulties, and create a more behaviorally consistent model. These changes to the model design moved GreenSTEP out of the realm of sketch-planning models. Most of GreenSTEP operates at an individual household level where each household has individual attributes and where vehicle ownership and use is predicted on an individual household basis.

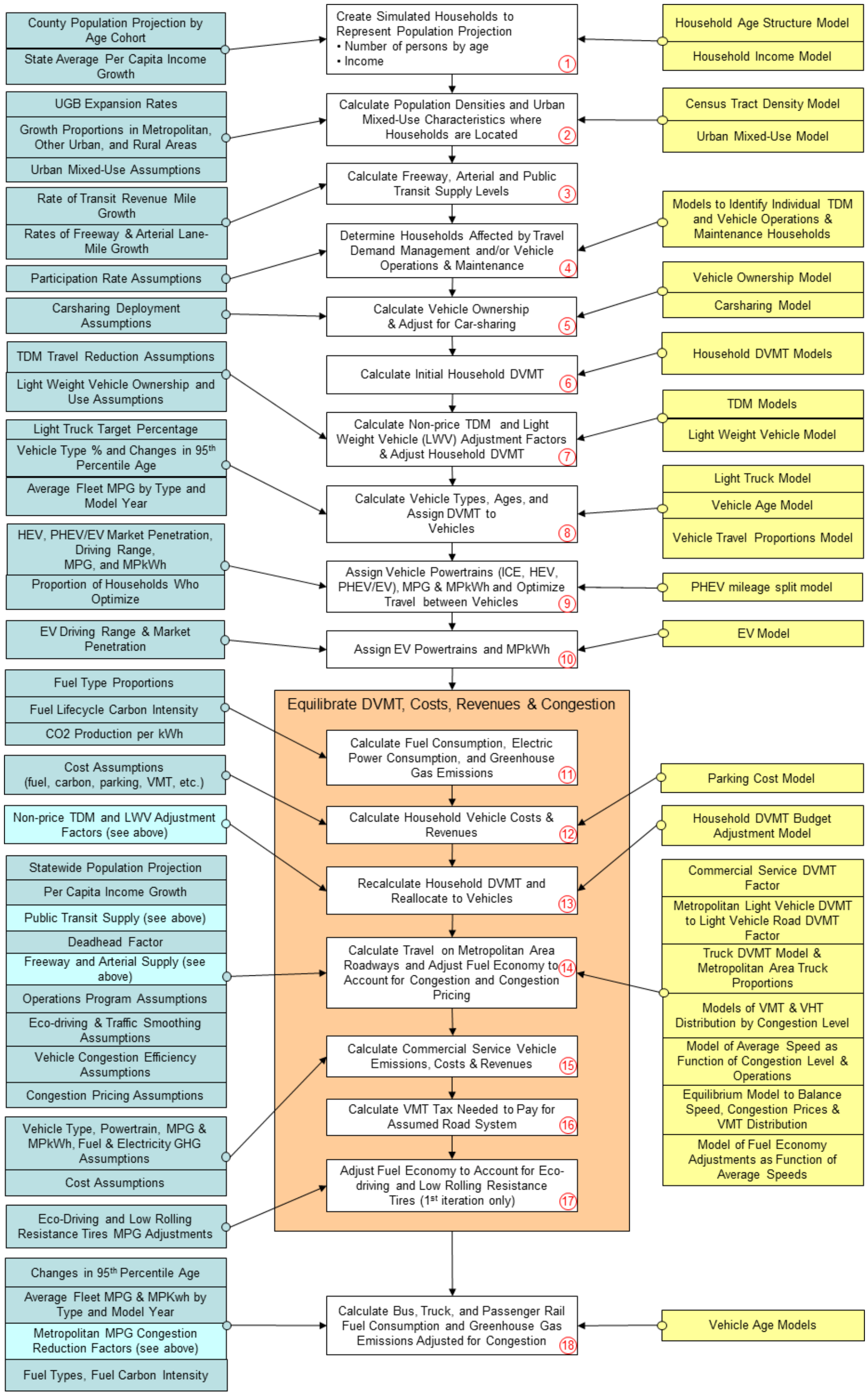
An advantage of this approach over a sketch planning approach is that it better accounts for interactions between policies. For example, a policy that increases urban area density decreases household daily vehicle miles traveled (DVMT) by shortening trip distances and increasing the proportion of non-auto travel. Higher densities also increase the market for car sharing. Increased car sharing in turn reduces household vehicle ownership, which also reduces household DVMT. Reducing household DVMT also increases the likelihood that a household vehicle could be replaced by an electric vehicle (EV) and increases the proportion of a plug-in hybrid electric vehicle (PHEV) owner's mileage that can be traveled on an electric charge. Modeling these types of interactions is not possible with a sketch-planning model approach.

Another benefit of the disaggregate approach is that it provides a means for accounting for the effects of changes in fuel prices and a number of other costs of household travel in a consistent manner. Because household fuel costs are a function of household vehicle fuel economy, the model accounts for increases in travel that would occur with gains in fuel economy (rebound effect).

Finally, modeling at the individual household level allows for better analysis of how different households would be affected by policies in a number of ways.

Figure 1 shows an overview of the current version 3.5 GreenSTEP and RSPM model design. The white boxes in the middle of the figure identify the major steps in the model execution. The number in the lower right-hand corner of each box corresponds to paragraph numbering in the description that follows. The blue boxes on the left side of the figure show the input assumptions on which the calculations are based and that may be altered to represent different policies. The yellow boxes on the right side of the figure identify the models and calculation methodologies that used in the calculations. These models and how they were estimated and calibrated are explained in this document.

FIGURE 1. DESIGN OF MODEL FOR ESTIMATING GHG FROM PASSENGER AND TRUCK TRAVEL



Following is an explanation of major steps in the model execution shown in the white boxes in the figure.

1. ***Create Simulated Households***: A set of households is created for each forecast year that represents the likely household composition for each county (GreenSTEP) or metropolitan area division (RSPM) given the forecast of persons by age for the area. Each household is described in terms of the number of persons in each of six age categories residing in the household. A total household income is assigned to each household given the ages of persons in the household and the average per capita income of the region where the household resides.

2. ***Calculate Population Densities and Other Land Use Characteristics***: Population density and land use characteristics are important variables in the vehicle ownership, vehicle travel, and vehicle type models. These models were estimated using the values of density and land use characteristics at the Census tract level. The approaches differ for the GreenSTEP and RSPM models. For GreenSTEP, each household is randomly assigned to a metropolitan, other urban, or rural development type based on policy assumptions about what proportions of population growth will be of each type. The overall densities for metropolitan and other urban areas in each county are calculated based on policy assumptions for urban growth boundary expansions. Households assigned to metropolitan areas are assigned to population density drawn from a likely Census tract density distribution corresponding to the overall metropolitan area density for the statewide model or to the district density for the metropolitan model. Households assigned to other urban areas are assigned the overall population density for non-metropolitan areas in the county. Households assigned to rural areas are assigned a population density reflecting the predominant rural population density of the county where it is located. Households in urban areas are also assigned to an urban-mixed use setting or not, based on a model using population density. This can be overridden to simulate greater amounts of urban mixed-use development. For the RSPM, existing or prospective numbers of dwelling units by type are specified by district (Census tract or similar) as inputs. A housing model is applied to assign households to dwelling units in districts based on the number of dwelling units by type in each district, the household income, and an income attraction factor (calibrated for the base year). After all households have been assigned to districts, population densities are calculated and urban mixed-use development is assigned.

3. ***Calculate Freeway, Arterial and Public Transit Supply Levels*****:** The number of lane-miles of freeways and arterials is computed for each metropolitan area based on base-year inventories and policy inputs on lane-mile additions for future years. For public transit, the inputs specify base year transit revenue miles and transit revenue mile additions for future years. Inputs for each metropolitan area also specify the revenue mile split between electrified rail and buses.

4. ***Determine Households Affected by Travel Demand Management and/or Vehicle Operations and Maintenance Programs:*** Each household is assigned as a participant or

not in a couple of travel demand management (TDM) programs. Two general types of TDM programs are modeled: employee commute options programs, and individualized marketing programs. Employee commute options programs provide a number of services and incentives to encourage commuting to work by means other than single-occupant vehicles such as rideshare matching, free transit passes, and guaranteed ride home. Individualized marketing programs are outreach activities to households which identify options and provide encouragement for non-auto travel in their neighborhoods. Households are also assigned to vehicle operations and maintenance programs (e.g. eco-driving, low rolling resistance tires) based on policy assumptions about the degree of deployment of those programs and the household characteristics.

5. ***Calculate Vehicle Ownership and Adjust for Car-sharing***: Each household is assigned the number of vehicles it is likely to own based on the number of persons of driving age in the household, whether only elderly persons live in the household, the income of the household, and the population density where the household lives. For metropolitan households, vehicle ownership depends on the freeway supply, transit supply and whether the household is located in an urban mixed-use area. Households are identified whether as car-sharing participants or not based on household characteristics and policy assumptions about the deployment of car sharing. The number of vehicles owned by car-share households is reduced using a simple model.

6. ***Calculate Initial Household Daily Vehicle Miles Traveled (DVMT)***: The average DVMT for each household is modeled based on household information determined in previous steps. There are different models for households residing inside and outside of metropolitan (urbanized) areas. The metropolitan model is sensitive to household income, population density of the neighborhood where the household resides, number of household vehicles, whether the household owns no vehicles, the levels of public transportation and freeway supplies in the metropolitan area, the driving age population in the household, the presence of persons over age 65, and whether the neighborhood is characterized by mixed-use development. The non-metropolitan model is similar but does not include the transit supply, freeway supply, or mixed use variables.

7. ***Calculate Non-price TDM and Light Weight Vehicle Adjustment Factors and Adjust Household DVMT:*** Non-price TDM policies are grouped into two categories, workplace-oriented commute options programs and household-oriented individualized marketing programs. Household DVMT adjustment factors are calculated based on participation in these programs (determined in step #4) and assumptions regarding the average reductions in household DVMT that the programs produce. Adjustment factors are also calculated to account for the potential substitution of light-weight vehicle (LWV) travel for household DVMT. Light-weight vehicles are bicycles, electric bicycles and similar vehicles. The model predicts the potential amount of household DVMT that could be diverted to light-weight vehicle travel using a model of the amount of household vehicle travel occurring in single-occupant vehicle tours less than a specified length. This model is sensitive to household income, population density, household size, urban mixed-use

character, and average household DVMT. The amount of diversion is a function of this potential, assumptions about light vehicle ownership rates, and assumptions about the proportion of the potential diverted vehicle travel that may be suitable for light weight vehicle travel. After the TDM and LWV factors have been calculated, they are applied to the initial household DVMT estimates to produce adjusted estimates.

GreenSTEP also includes a walk model which estimates the daily number of walk trips for each household. This model was added to GreenSTEP in order to provide an indicator of the effect of land use and transportation policies on active transportation. The model does not affect the amount of household DVMT because the land use and transportation policies affect the calculations of DVMT directly.

8. ***Calculate Vehicle Types, Ages, and Initial Assignment of DVMT to Vehicles***: Two body styles of household vehicles are considered - automobiles and light trucks. The latter includes pickup trucks, sport-utility vehicles and vans. A model predicts the probability that a household vehicle is a light truck based on the number of vehicles in the household, the household income, the population density where the household resides, and whether the household lives in an urban mixed-use area. This probability is then used as a sampling probability to determine stochastically whether each household vehicle is an automobile or light truck. Once the type of vehicle has been assigned to each vehicle, the age of each vehicle is determined. This is done by sampling from vehicle age distributions by vehicle type and household income group. These distributions may be changed based on input assumptions about changes in fleet turnover rates. Vehicles are assigned a proportion of the estimated household DVMT based on distributions of how annual household mileage is allocated among multiple vehicle households. The initial assignments are made by random draws from these distributions without regard to vehicle characteristics. Later, in step #9, the allocations are optimized to maximize household fuel economy.

9. ***Assign Vehicle Powertrain and Optimize Travel between Vehicles:*** Household vehicle powertrains are identified as being either internal combustion engines (ICE), hybrid electrics (HEV), plug-in hybrid electrics (PHEV), or battery electrics (EV). This is done in 2 steps. The first step partitions vehicles between an ICE/HEV category and a PHEV/EV category. This partitioning is based on input assumptions about market penetration by model year and vehicle type (auto vs. light truck) using a Monte Carlo process. Vehicles identified as ICE/HEV are partitioned into constituent categories in the same way. The PHEV/EV category is partitioned in Step #10. All vehicles in the PHEV/EV combined category are treated as PHEV for the purpose of assigning MPG and miles per kilowatt-hour (MPkWh) in this step. MPG and MPkWh are assigned from input assumptions by powertrain, vehicle type, and model year. Once powertrain has been assigned, travel is optimized. The input assumption on the proportion of households that are optimizers is used in a Monte Carlo process to determine which households will optimize vehicle usage to maximize fuel economy. For optimizing households, VMT proportions are ordered in the order of vehicle fuel economy. It should be noted that this process does

not change the sizes of the proportions of household vehicle VMT. It only changes which household vehicle is assigned to each proportion. For PHEVs a fuel economy equivalent is calculated based on the battery range of the PHEV, a fuel economy equivalent for electric operation, and the MPG for non-electric operation. Also for PHEVs, the proportion of travel “fueled” by the power grid vs. on-board hydrocarbon fuels is calculated. This is done using a model which predicts the proportion of PHEV travel that is likely to be powered by electricity stored in the vehicle battery based on the range of battery operation, household income, population density, number of household vehicles, transit service level, number of driving age persons in the household, number of elderly persons in the household, and whether the household is located in an urban mixed-use neighborhood.

10. ***Assign Electric Vehicles (EVs) and Calculate Adjustments to Fuel and Electric Power Consumption***: EV vehicles are identified from the pool of PHEV vehicles based on how their vehicle usage patterns compare with the average travel range of EVs for their vehicle model years. A vehicle is only considered to be a candidate to be an EV if the vehicle range is large enough to accommodate most of the expected usage of the vehicle by the household. To determine this, the 95th percentile DVMT is determined for each vehicle as a function of the average DVMT of the vehicle. Candidate vehicles are then identified as EVs based on input assumptions regarding the market penetration of EVs among candidate vehicles. EVs are only selected from the pool of vehicles previously identified as PHEV so that the optimization considerations in step #9 would be close to representing EV efficiency.

Calculate Emissions and Equilibrate Household Travel, Travel Costs, Metropolitan Area Congestion and Road Revenue: Steps 11-18 equilibrate the amount of household travel with travel costs, metropolitan area congestion, and road revenue. Up to this point in the process, estimates of household VMT do not reflect travel costs. The equilibration steps calculate household vehicle variable costs (gas, taxes, electricity, parking, congestion) and adjust the amount of household vehicle travel based on a household budget model. The same sequence of steps also balances traffic on metropolitan area road classes (freeway, arterial, local) based on relative capacities and speeds and congestion pricing. Congestion prices are reflected back into household travel costs. The third balancing act in this sequence of steps is to balance public road revenues and costs. Fees are adjusted so that the assumed road infrastructure for a scenario is paid for by road users and that road user travel budgets reflects respond to those costs. This latter functionality is important for evaluating scenarios on a consistent basis. Otherwise, for example, a scenario that postulates a large shift in the vehicle fleet to high MPG and electric vehicles would overestimate VMT and underfund the transportation system because road user fees would be inadequate to fund the road system and road users would not be experiencing the cost that they inevitably would have to pay in order to maintain, operate and construct the road system. This latter equilibration of road system costs and road user fees can be turned off enable estimation of the deficit between road revenues and costs. It is possible to turn off this balancing process, and this is most often done for RSPM applications because costs and revenues are more often balanced at a statewide level and not at a metropolitan area level.

11. ***Calculate Fuel Consumption, Electric Power Consumption, and Greenhouse Gas Emissions:*** Fuel consumption is calculated for ICE, HEV, and the fuel-powered portion of PHEV vehicles based on the fuel economy values assigned to each vehicle in step #9 and the annual vehicle miles traveled for the vehicle. Similarly, the electric power consumption for the electric portion of PHEV travel is based on the power efficiency of the vehicle and annual vehicle miles traveled powered by electricity. Fuel consumption is converted to greenhouse gas emissions based on the assumed fuel mix for the future year and the carbon intensity for each fuel. Electric power consumption is converted to greenhouse gas emissions based on the amount of electrical power consumed and the assumed rates of greenhouse gas emissions per unit of power consumed. The emission rates for fuel and electric power include emissions arising from production and transmission of the fuel or power as well as emissions from the vehicle itself as a result of combusting the fuel.

12. ***Calculate Household Mileage Costs and Revenues:*** Total variable vehicle costs (costs that vary based on vehicle usage) are calculated for each household. These costs include the cost of fuels and electrical power. They may also include, depending on policy assumptions, carbon taxes, VMT taxes, pay-as-you-drive (PAYD) insurance rates, and parking charges. Both out-of-pocket and externality (e.g. pollution) costs are computed. Externality cost rates (e.g. per VMT or per gallon) must be provided as a model input. The model inputs also specify what proportion of the externality costs will be paid by road users through taxes or fees. Externality costs that are paid through taxes or fees are added to the household out-of-pocket costs. For metropolitan areas, a model is applied to determine how many working age persons in each household pay for parking at their worksite based on input assumptions about the proportion of employees in the metropolitan area have employers who charge for parking or who must pay for parking at commercial lots, and how easily the parking charges may be avoided by parking for free on the street or free parking lots. The model also estimates the portion of non-work household trips that another model calculates daily parking charges for households paying for employment parking and other trip parking. This step also estimates fixed vehicle costs (e.g. depreciation, financing) but this is for reporting purposes only. The vehicle budget used to adjust DVMT is only the variable vehicle cost budget. Road revenues from highway gas taxes and mileage fees are calculated as well.

13. ***Recalculate Household DVMT and Reallocate to Vehicles***: A household budget model is used to adjust household DVMT to reflect the effect of variable vehicle costs on the amount of household travel. The adjusted household DVMT is allocated to vehicles in proportion to the previous allocation. The travel reduction proportions from TDM and light-weight vehicle use calculated in step #7 are applied.

14. ***Calculate Travel on Metropolitan Area Roadways and Adjust Fuel Economy to Account for Congestion Effects:*** Since roadway congestion affects vehicle speeds and fuel economy, it is necessary to calculate total roadway VMT in metropolitan areas. Commercial service vehicle VMT is calculated and added to household light-duty vehicle VMT to estimate total light vehicle VMT due to household and business activities in the metropolitan area (see step #15 below for more on commercial service vehicles). Light-duty vehicle VMT on metropolitan area roads is calculated by applying a factor calculated for the base year (2005) that is the ratio of urbanized area light-duty vehicle DVMT calculated from Highway Performance Monitoring System (HPMS) data and this estimate of total household and commercial service vehicle VMT. Metropolitan area heavy truck VMT is calculated from a statewide heavy truck VMT forecast that is based on changes in the total state income. As a default, a one-to-one relationship between state income growth and heavy truck VMT growth is assumed. In other words, a doubling of total state income would result in a doubling of heavy truck VMT. Portions of the statewide heavy truck DVMT are assigned to metropolitan areas based on proportions estimates derived from HPMS data. Bus DVMT is calculated from bus revenue miles that are factored up to total vehicle miles to account for miles driven in non-revenue service. Bus and truck DVMT are allocated each of 3 road classes using base year proportions.

    Light-duty vehicle VMT is allocated to the road classes (freeway, arterial, other) based on a model which equilibrates traffic flows and speeds. VMT by road class is allocated to five congestion levels based on the ratio of total VMT to lane-miles for each road class. Each freeway and arterial congestion level is associated with an average trip speed. Speeds are adjusted based on scenario assumptions regarding the deployment of traffic operations programs. Average speeds for VMT in congestion are adjusted for congestion pricing based on conversion of cost to speed based on an assumed average value of time. VMT is split between freeways and arterials based on a function of the ratios of their average speeds. This cycle is repeated until there is no change in the distribution of VMT between arterials and freeways.

    Speed vs. fuel efficiency relationships for light vehicles, trucks and buses are used to adjust the fleet fuel efficiency averages. The adjustment functions are sensitive to the vehicle powertrain and to input assumptions regarding the congestion efficiency of vehicles in the fleet by year.

15. ***Calculate Commercial Service Vehicle Fuel Consumption, Emissions, Costs, and Revenues:*** Commercial service vehicles are light and medium duty vehicles used for commercial purposes such as deliveries, service and repair calls, and other business travel. Commercial service vehicle VMT is calculated for the base year as a fixed proportion of household VMT. The proportion is calculated in model calibration by comparing the base year statewide GreenSTEP estimate for household VMT with an overall estimate of estimate of light-duty vehicle VMT for the road system in the state. Based on this estimate, a ratio is calculated between the commercial service vehicle

VMT and the total household income. This ratio is then used in forecasting to compute commercial service vehicle VMT from total household income. Commercial service vehicle VMT is split into vehicle types and powertrains based on scenario input assumptions. The distribution of vehicle ages reflects inventory values and scenario input assumptions about changes to the vehicle age structure. Fuel economy by vehicle type and powertrain is taken to be the same as equivalent household vehicles. Fuel types (e.g. gasoline, diesel, CNG) are based on scenario input assumptions. The calculation of fuel consumption rates and emissions reflect the metropolitan area congestion adjustment factors for the proportion of commercial service vehicle travel estimated to occur within metropolitan areas. Commercial service vehicle variable costs and revenues from taxes/fees on commercial service vehicle travel are calculated in the same manner as household vehicle costs.

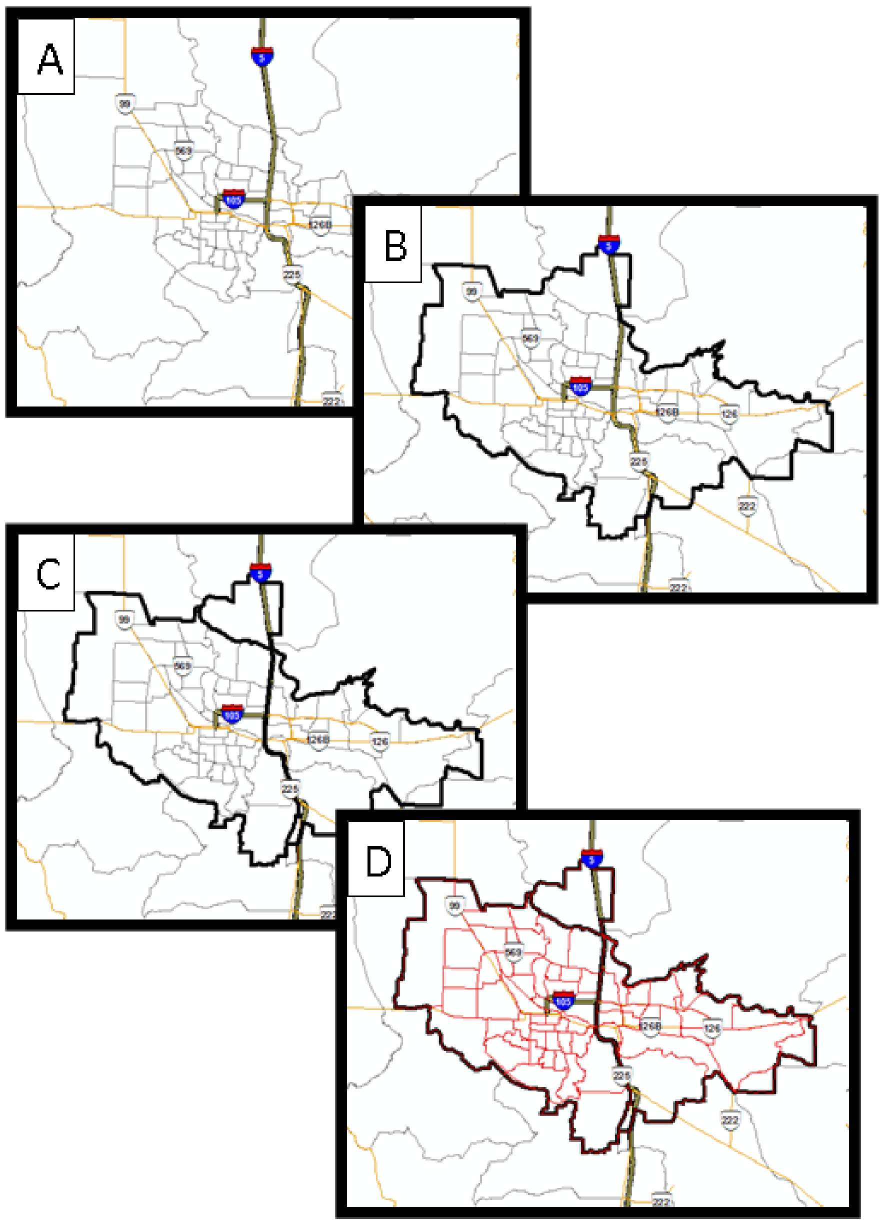
16. ***Calculate VMT Tax Needed to Pay for the Assumed Road System:*** The annual cost of maintaining, operating, repairing and modernizing the road system for a scenario are estimated from annual VMT and annualized lane-mile expansion costs. The annual VMT-based costs cover maintenance, operations, repair, reconstruction and minor modernization. The annualized lane-mile expansion costs cover expansions of freeway and arterial lane miles. The light vehicle proportion of the costs is calculated as a function of the light and heavy vehicle VMT and the passenger car equivalents for the heavy vehicle VMT. The total annual cost attributable to light vehicles is compared to the total revenue from household and commercial service vehicle travel for road purposes (gas tax and VMT tax). If the total light vehicle road revenues are less than the total road costs, a VMT charge is calculated that would balance out revenues and costs.

17. ***Adjust Fuel Economy to Account for Eco-driving and Low Rolling Resistance Tires***: The average fuel economy of households identified as eco-drivers is adjusted based on assumed adjustment rates. Adjustment to fuel economy and power consumption is also made for households identified as having low rolling-resistance tires on their vehicles. This is done only for the first iteration of the equilibration process.

18. ***Calculate Bus, Truck, and Passenger Rail Fuel Consumption and Greenhouse Gas Emissions Adjusted for Congestion***: The age distributions of trucks and buses are computed from base year distributions and input assumptions about changes in fleet turnover. The average MPG of the respective fleets is computed from the respective age distributions and respective assumptions about future MPG by model year. These fuel economy values are adjusted for the truck and bus VMT in metropolitan areas using the adjustment factors computed in step #14.

As noted earlier, GreenSTEP and the RSPM represent geography differently. In the case of GreenSTEP, counties and metropolitan areas are the geographic units for which data are input. Counties are used because many data items are published at the county level. Other geographic areas such as the US Census Bureau's Public Use Microsample Areas (PUMA) could be used instead if the data items are available. Metropolitan area data are also used to calculate density, urban mixed use development, roadway supply, and transit supply. The RSPM does not use county geography. Instead, it divides the metropolitan area into two geographic levels; districts and divisions. Districts are the smallest geographic units. They represent neighborhoods and are approximately the size of census tracts. Divisions are aggregations of districts which represent large political or geographic subdivisions of the metropolitan area. As with GreenSTEP, some of the inputs for the RSPM are provided at the metropolitan area level. Other inputs are provided at the division or district levels. These areas are illustrated in Figure 2. Panel A shows the metropolitan area and its environs. Panel B shows the boundary of the metropolitan area that is modeled. Panel C show the metropolitan area split into 3 divisions. Panel D shows those divisions divided into 68 districts.

FIGURE 2. ILLUSTRATION OF RSPM GEOGRAPHY



Model Implementation Platform

The GreenSTEP and RSPM models are implemented in the R programming language[1]. R is an open source version of the S language developed at Bell Laboratories by Chambers et al. ODOT has had a substantial amount of experience and success using R for developing and implementing transportation and land use models. R is used for implementing small urban area travel demand models (OSUM), metropolitan area travel demand models (JEMnR), a stochastic land use model (LUSDR), and the land development module of the statewide model (ALD). In addition, ODOT uses R for routine data manipulation and analysis, and the analysis and visualization of model results. Scenario inputs are described in several text files. Once the text files and the proper directory structure have been created, the model is run with a single controlling run script. R scripts have also been developed to create and run large numbers of sensitivity scenarios and to create outputs that can be dynamically queried and visualized in a web browser-based application, for example: http://www.oregon.gov/ODOT/Planning/Pages/PTV-SV.aspx?sv=CAMPO.

Model Estimation Data

Several sources of data were used to estimate the component models of GreenSTEP. The U.S. Census public use micro-sample (PUMS) data for Oregon, and 2009 vehicle data for Oregon from the Driver and Motor Vehicle Services (DMV) Division of ODOT were used for a few model components. A few other ancillary data sources were used in several model components. They are described in the sections of the report describing the models they were used to estimate.

A number of the models were estimated from datasets created from the 2001 National Household Travel Survey (NHTS) data. The 2001 NHTS datasets that are available for download from the internet (https://nhts.ornl.gov/download.shtml) were used. The model estimation process used data from the household (HHPUB.csv), vehicle (VEHPUB.csv), person (PERPUB.csv), daily trip (DAYPUB.csv), and long-distance travel (LDTPUB.csv) files. Following are summary descriptions of important variable transformations made prior to model estimation.

The data include estimates of annual vehicle VMT. However, since these data are included for less than half of the records and have data quality problems, DVMT was computed for each household from the person trip file for person trips where the:

- Trip had a recorded mileage;
- Person was not identified as a passenger;
- Travel conveyance was a private vehicle (e.g. auto, SUV etc.); and
- Speed as measured by recorded distance divided by recorded time is reasonable.

[1] R Core Team (2012). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

The auto ownership variable (Ratio16v) in the NHTS was found to be incorrect. This variable records the ratio of driving age persons to vehicles in the household. The variable is coded with a value of zero rather than infinite for households that own no vehicles. To correct this problem, a new variable was created that is the ratio of vehicles to driving age persons. This variable has a zero value for households that own no vehicles.

Freeway and arterial supplies (lane-miles per capita) for identified metropolitan areas were tabulated from the 2001 Highway Statistics data. Similarly, transit revenue miles per capita were calculated for each of these metropolitan areas from the National Transit Database for 2001. The NHTS data, however, only identify metropolitan areas that have populations of one million or more. The identities of smaller metropolitan areas are not disclosed. Since freeway lane-miles and transit revenue miles were identified as significant and important predictors of vehicle ownership and vehicle travel for metropolitan households, it is important to include them in the model estimations. This means that the estimated metropolitan models are only based on the larger metropolitan area data. Given that several of the larger metropolitan areas identified in the data are low density auto-oriented areas, it is reasonable to use the metropolitan area models estimated using the larger metropolitan area dataset for smaller metropolitan areas as well.

Create Simulated Households

Household Age Structure

Forecasts of population by age are primary inputs to the GreenSTEP and RSPM models. The forecasts are transformed into a set of household records where each household is defined by the number of persons in each of six age categories in the household (0 – 14, 15 – 19, 20 – 29, 30 – 54, 55 – 64, 65+). This household simulation process is commonly used in modeling to represent the aggregate characteristics of a population as well as the diversity of household characteristics that are present in a population.

The household simulation process uses a combination of probabilities derived from the PUMS 2000 data for Oregon (76,516 records) and an iterative proportional fitting (IPF) process to create a balanced set of households. The PUMS data were used to create a set of household types defined by the number of persons in each of the six age groups identified above. For example, a household having two children under 15 years of age and two adults in the 30 to 54 age group could be represented as type 2-0-0-2-0-0. The number of household types represented in the PUMS data is large and the set of all possible types is very large. However, many of the types constitute a very small portion of all households. Building a model to account for all these household types would require many additional calculations (slowing the model down appreciably) and would add little to model accuracy. Therefore, the maximum number of persons in each age category was capped at values that account for 99 percent of all households. Using this criterion, the 0 to 14 age category was capped at four and all other age categories were capped at two. This put the theoretical limit of the number of household types at 1215. Only 525 of these types are present in the PUMS data, and 83 of the records identify the household as being composed of persons all under the age of 15. These were removed, which left 524 household types included in the model.

Since the PUMS data associates person information with household information, the probabilities that persons of each age group can be found in households of each type can be easily computed. These probabilities serve as the starting basis for developing a representative forecast of households for a county given the age cohort population forecast for the county. This is not sufficient, however, since household types are a joint characteristic of several persons, not individual persons.

Multiple estimates of households by type result from the application of the probabilities for each person age group. An IPF process was used to reconcile the household type estimates and create a consistent set of households. The first control for the IPF process is to match the population forecasts by age category. Since each household type has a corresponding population age distribution (e.g. type 2-0-0-2-0-0 has 2 persons under age 15 and 2 persons between 30 and 54 years old), the overall age distribution of the synthetic households can be tabulated and compared to the input age distribution. The second control is to create a consistent forecast of the number of households of each type as explained below. Each iteration is comprised of the following steps:

1. Persons of each age group are allocated to households by type by applying the calculated probabilities to the number of persons in each age category.
2. The persons allocated by household type are converted to households by type by dividing persons in each age category and type by the corresponding persons by age for that household type. For example, 100 persons of age 0 – 14 allocated to household type 2-0-0-2-0-0, implies 50 households of that type.
3. The result of step #2 will be several conflicting estimates of the number of households of each type. Two methods may be used to resolve the differences in the estimates. The "min" method chooses the minimum of the estimates, and the "mean" method chooses the average of the estimates. Both methods work with the PUMS data, but when applied to historical population data by county, the “min” method does not reach convergence reliably.
4. The resolved number of households for each type computed in step #3 is multiplied by the corresponding number of persons in each age group to yield an estimate of the number of persons by age group and household type.
5. A new table of household type probabilities for each age group is computed from the step #4 tabulation.
6. The sum of persons by age group is calculated from the results of step #4 and subtracted from the control totals of persons by age group to determine the difference to be reallocated.
7. The person differences are allocated to household types using the probabilities calculated in step #5.

These steps are repeated until the difference between the maximum number of households and the resolved number of households computed for every household type is less than 0.1 percent or until a maximum number of iterations (default 100).

This process was applied to the PUMS data using both the “mean” and “min” methods for resolving household estimates. Table 1 compares observed and estimated numbers of households using the “min” method where the difference in number of households is greater than 10. Table 2 is a similar comparison using the “mean” method.

This test shows that either method reproduces the household composition of the PUMS data reasonably well. Out of 524 household categories, less than 20 have model estimates that vary from the observed numbers by more than 10. Overall, the "mean" method for resolving conflicts in the IPF appears to do a better job of reproducing the PUMS tabulations. It has fewer household types that differ from PUMS by more than 10 (17 vs. 19). The range of errors of household types that are off by more than 10 is also lower for the "mean" method. The maximum value difference for the "mean" method is 249 compared to 320 for the "min" method. The maximum percentage difference for the "mean" method is 21 per cent compared to 35 per cent for the "min" method.

TABLE 1. COMPARE PUMS AND MODEL HOUSEHOLD TYPES USING THE "MIN" METHOD

HhType	PUMS	Model	Difference	Ratio
0-0-0-0-0-1	7332	7355	23	100.31
0-0-0-0-0-2	5037	5089	52	101.03
0-0-0-1-0-0	7461	7537	76	101.02
0-0-0-2-0-0	6439	6605	166	102.58
0-0-1-0-0-0	2471	2593	122	104.94
0-0-1-1-0-0	1253	1266	13	101.04
0-0-2-0-0-0	2230	2550	320	114.35
0-1-0-0-0-0	907	1024	117	112.90
0-1-0-2-0-0	1290	1303	13	101.01
0-1-1-0-0-0	231	242	11	104.76
0-2-0-0-0-0	80	108	28	135.00
0-2-0-2-0-0	630	642	12	101.90
1-0-0-2-0-0	2411	2436	25	101.04
1-0-2-0-0-0	938	957	19	102.03
1-1-0-2-0-0	1251	1264	13	101.04
2-0-0-2-0-0	3288	3322	34	101.03
2-0-2-0-0-0	703	717	14	101.99
3-0-0-2-0-0	1226	1239	13	101.06
4-0-0-2-0-0	462	474	12	102.60

TABLE 2. COMPARE PUMS AND MODEL HOUSEHOLD TYPES USING THE “MEAN” METHOD

HhType	PUMS	Model	Difference	Ratio
0-0-0-0-0-2	5037	5076	39	100.77
0-0-0-1-0-0	7461	7484	23	100.31
0-0-0-2-0-0	6439	6558	119	101.85
0-0-1-0-0-0	2471	2522	51	102.06
0-0-1-1-0-0	1253	1268	15	101.20
0-0-1-2-0-0	698	720	22	103.15
0-0-2-0-0-0	2230	2479	249	111.17
0-0-2-1-0-0	188	207	19	110.11
0-0-2-2-0-0	166	178	12	107.23
0-1-0-0-0-0	907	920	13	101.43
0-1-0-2-0-0	1290	1306	16	101.24
0-1-2-0-0-0	101	113	12	111.88
0-2-0-0-0-0	80	97	17	121.25
0-2-0-2-0-0	630	655	25	103.97
1-0-2-0-0-0	938	960	22	102.35
2-0-2-0-0-0	703	717	14	101.99
4-0-0-2-0-0	462	485	23	104.98

The household simulations were also tested with county population estimates and forecasts by age group. When applying a similar function that only used the “min” method, the IPF did not converge for some counties and some years. Table 3 shows the results of using the “min” and “mean” methods to synthesize households using 1990 population estimates. The results show that the “min” method took much longer to execute and did not achieve closure for 35 of 36 counties. The “mean” method achieved closure for all counties and the maximum difference (for all counties) between the minimum number of households of each type and the mean number was 36.

TABLE 3. COMPARISON OF 'MIN' AND 'MEAN' MODEL METHODS USING 1990 COUNTY POPULATION DATA

Method	Run Times (seconds)	Number of Counties For Which Maximum Iterations Were Exceeded	Maximum Convergence Error
min	122.15	35	100
mean	53.99	0	36

In the case of the RSPM, the simulated households are created for each division based on the respective division population projections. Moreover, the user may set targets for the average household size and the proportion of one-person households for each division. The IPF procedure will then match these constraints as well as the constraints described above. This enables the RSPM to better match the household characteristics of the subject metropolitan area.

The data files and R scripts used to estimate the household age model are contained in the “hh_age_model” directory of the estimation files repository for the version 3.5 model.

Household Income

A regression model was developed to predict average household income based on the number and ages of persons in the household and the average per capita income for the county (or division for RSPM) where the household resides. Data used to develop the model included:

- US Census Bureau Public Use Micro-Sample (PUMS) data for Oregon for the year 2000;
- Bureau of Economic Analysis (BEA) personal income and employment data (Table C04) income data by county for the years from 1990 to 2012.
- US Census Bureau Small Area Income and Poverty Estimates (SAIPE) county level data for Oregon for the years 1989 to 2012 (https://www.census.gov/did/www/saipe/data/statecounty/data/index.html)

All income data were deflated to year 2005 dollars.

The entire PUMS data sample was used to estimate the model. This was a significant change in the methodology used to estimate the model in previous versions of GreenSTEP. Previously, only data for households having annual incomes less than 150 thousand dollars were used in the mistaken belief that a stronger model would be estimated by truncating the right-hand tail. Unfortunately that approach contributed to a model result which underestimated household income significantly (i.e. the average per capita income calculated from the model outputs is significantly less than the average that is input to the model).

The distribution of household income is highly skewed with a long right-hand tail. A power transformation was used to normalize the income data and a linear regression model of transformed income was estimated. A binary search process was used to find the exponent which minimizes the skewness of the population. This was found for Oregon to be 0.1909. (The previous model with a truncated right-hand tail used an exponent of 0.4.)

Five model forms were estimated. Each was estimated with and without an intercept term:

- No interactions between independent variables.
- The income variable is interacted with each of the age variables. Only interacted variables are included.
- The income variable is interacted with each of the age variables. Non-interacted variables are also included.
- The income variable is interacted with each of the age variables. Non-interacted variables are included except for the income variable.
- The income variable is interacted with each of the age variables. The non-interacted age variables are excluded but the non-interacted income variable is included.

Four models were estimated for each model form. These differed with respect to the type of income variable (average per capita income vs. median per capita income) and the level of disaggregation (Portland metropolitan area aggregated or disaggregated). The models are designated as follows:

- More aggregate per capita income
- More disaggregate per capita income
- More aggregate median income
- More disaggregate median income

Several linear models were estimated to predict the power transformed income as a function of the structure of the household and the average per capita income of the county where the household resides. The previous model had used the per capita income for larger economic regions. As might be expected, the use of county per capita income enables modeled household income to better match at the county level. Several linear model forms were estimated and compared. These models differed with respect to:

- The independent variable: mean vs. median income;
- The specification of interactions between the age and per capita income terms;
- The use or not of an intercept term; and,
- The level of geographic disaggregation for per capita income (county vs. economic area).

These models are documented in the “estimate_income_model.r” script contained in the “hh_income_model” directory of the of the estimation files repository for the version 3.5 model.

The following four models using the more disaggregate average per capita income specification and no intercept were chosen for further testing. Results are shown in Tables 4 – 7.

1. Previous model specification;
2. New model, no interaction terms, mean income;
3. New model, interaction terms, mean income; and,
4. New model, interaction terms, median income.

Table 4. Model 1: Previous Model Specification, Mean Income

```
lm(formula = PowHinc ~ PowPerCapInc2 + Age0to14 + Age15to19 +
    Age20to29 + Age30to54 + Age55to64 + Age65Plus + 0)

Residuals:
     Min       1Q   Median       3Q      Max
-108.471  -11.151    0.135   11.043   67.535

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
PowPerCapInc2  0.802499   0.003185  251.96  < 2e-16 ***
Age0to14      -1.040379   0.077058  -13.50  < 2e-16 ***
Age15to19      0.892334   0.148980    5.99 2.11e-09 ***
Age20to29      7.701869   0.119628   64.38  < 2e-16 ***
Age30to54     15.107392   0.112148  134.71  < 2e-16 ***
Age55to64     12.997139   0.148901   87.29  < 2e-16 ***
Age65Plus      8.253668   0.139203   59.29  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 17.34 on 63502 degrees of freedom
Multiple R-squared:  0.9412,  Adjusted R-squared:  0.9412
F-statistic: 1.452e+05 on 7 and 63502 DF,  p-value: < 2.2e-16
```

Table 5. Model 2: New Model, No Interaction Terms, Mean Income

```
lm(formula = PowHinc ~ PowPerCapInc2 + Age0to14 + Age15to19 +
    Age20to29 + Age30to54 + Age55to64 + Age65Plus + 0)

Residuals:
    Min      1Q  Median      3Q     Max
-6.2044 -0.6165  0.0167  0.5960  5.4168

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
PowPerCapInc2  0.897436   0.001655 542.313  < 2e-16 ***
Age0to14      -0.046736   0.004654 -10.042  < 2e-16 ***
Age15to19      0.049716   0.008983   5.535 3.13e-08 ***
Age20to29      0.410648   0.007266  56.519  < 2e-16 ***
Age30to54      0.868999   0.006790 127.988  < 2e-16 ***
Age55to64      0.786912   0.008968  87.748  < 2e-16 ***
Age65Plus      0.512288   0.008457  60.573  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.068 on 65983 degrees of freedom
Multiple R-squared:  0.9801,  Adjusted R-squared:  0.9801
F-statistic: 4.647e+05 on 7 and 65983 DF,  p-value: < 2.2e-16
```

TABLE 6. MODEL 3: NEW MODEL, INTERACTION TERMS, MEAN INCOME

```
lm(formula = PowHinc ~ 0 + PowPerCapInc2 * (Age0to14 + Age15to19 +
    Age20to29 + Age30to54 + Age55to64 + Age65Plus) - Age0to14 -
    Age15to19 - Age20to29 - Age30to54 - Age55to64 - Age65Plus)

Residuals:
    Min      1Q  Median      3Q     Max 
-6.3748 -0.6149  0.0190  0.5993  5.4258 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
PowPerCapInc2            0.8969393  0.0016591 540.631  < 2e-16 ***
PowPerCapInc2:Age0to14  -0.0065830  0.0006743  -9.762  < 2e-16 ***
PowPerCapInc2:Age15to19  0.0076806  0.0013019   5.899 3.67e-09 ***
PowPerCapInc2:Age20to29  0.0591554  0.0010482  56.435  < 2e-16 ***
PowPerCapInc2:Age30to54  0.1257915  0.0009826 128.025  < 2e-16 ***
PowPerCapInc2:Age55to64  0.1147261  0.0013051  87.907  < 2e-16 ***
PowPerCapInc2:Age65Plus  0.0747757  0.0012334  60.628  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.068 on 65983 degrees of freedom
Multiple R-squared:  0.9801,  Adjusted R-squared:  0.9801 
F-statistic: 4.648e+05 on 7 and 65983 DF,  p-value: < 2.2e-16
```

TABLE 7. MODEL 4: NEW MODEL, INTERACTION TERMS, MEDIAN INCOME

```
lm(formula = PowHinc ~ 0 + PowMedianHinc2 * (Age0to14 + Age15to19 +
    Age20to29 + Age30to54 + Age55to64 + Age65Plus) - Age0to14 -
    Age15to19 - Age20to29 - Age30to54 - Age55to64 - Age65Plus)

Residuals:
    Min      1Q  Median      3Q     Max 
-6.5807 -0.6180  0.0174  0.5946  5.4661 

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)    
PowMedianHinc2            0.8330544  0.0015370 542.008  < 2e-16 ***
PowMedianHinc2:Age0to14  -0.0072390  0.0006233 -11.613  < 2e-16 ***
PowMedianHinc2:Age15to19  0.0060001  0.0012037   4.984 6.23e-07 ***
PowMedianHinc2:Age20to29  0.0541225  0.0009702  55.784  < 2e-16 ***
PowMedianHinc2:Age30to54  0.1156759  0.0009097 127.158  < 2e-16 ***
PowMedianHinc2:Age55to64  0.1047488  0.0012079  86.720  < 2e-16 ***
PowMedianHinc2:Age65Plus  0.0678637  0.0011418  59.434  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.068 on 65983 degrees of freedom
Multiple R-squared:  0.9801,  Adjusted R-squared:  0.9801 
F-statistic: 4.649e+05 on 7 and 65983 DF,  p-value: < 2.2e-16
```

These models produce mean incomes that are significantly below the observed PUMS mean; about 78% of the observed mean for Model 1 and about 82% of the observed mean for the other models. The capping of income at $150 thousand in the model estimation dataset for the 1st model probably contributes to the larger amount of under prediction for that model. The modeled median values are much closer to the observed median; within 95 to 98 percent of the observed value. The coefficient of variation (CV) for the modeled incomes are about half of the CV for the observed values. The CV for Model 1 is substantially lower than the CVs for the new models. The explained variation for all of the models is under 20%, but the newer models (2-4) explain 72-82% more variation than Model 1.

There is a larger difference between the model averages and the BEA reported values. The averages from the models are 60%-63% of the BEA value. This reflects differences between the model predictions and the PUMS mean as well as differences between the PUMS mean and the BEA value. The PUMS mean is 77% of the BEA reported value. The under prediction of average income by the models is a combination of lower PUMS estimates and inadequate variance in the model estimates. Several factors most likely contribute to the underestimation of average income using PUMS data:

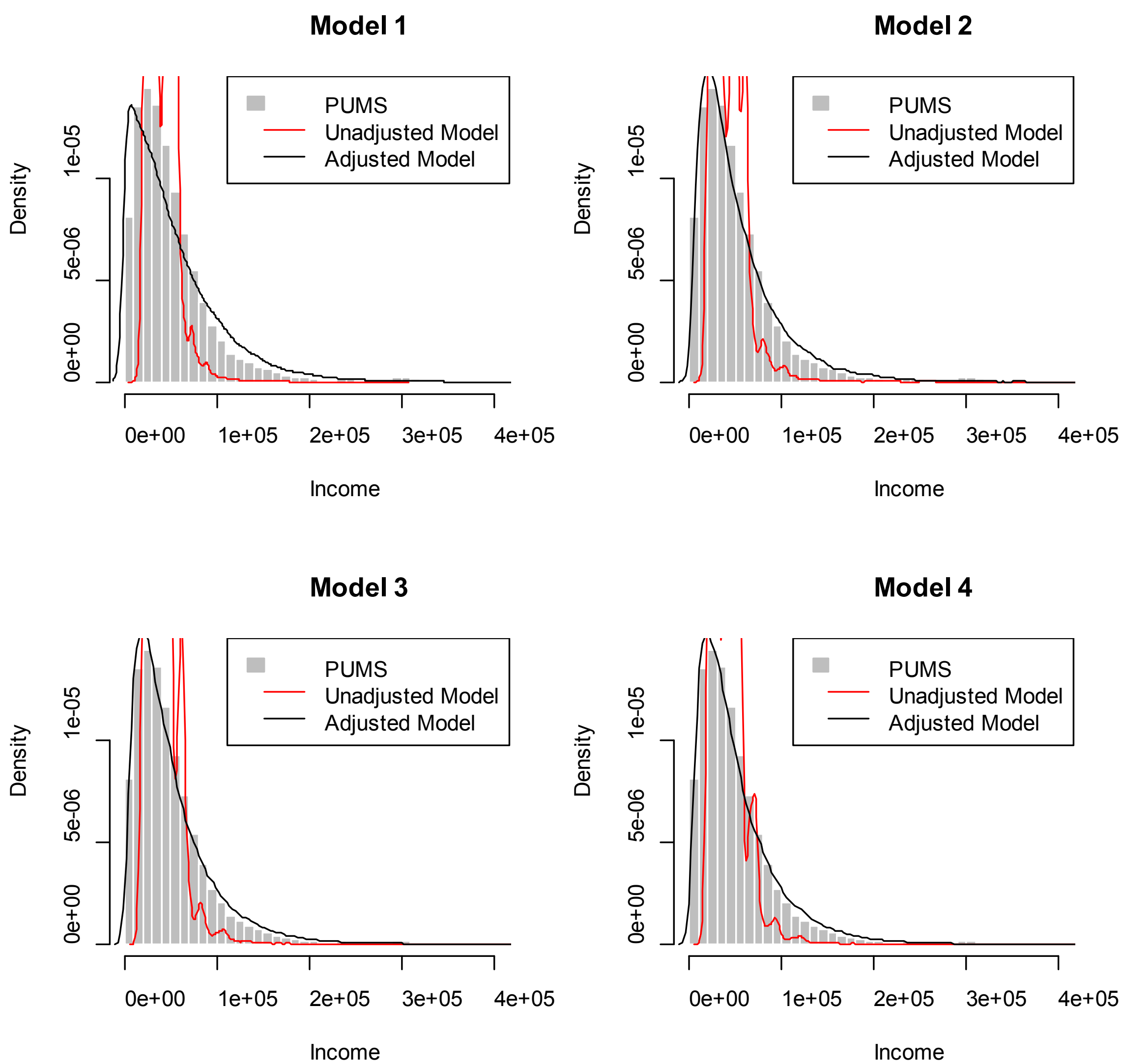
- PUMS income data does not include capital gains, a substantial source of income for the more affluent.
- There is a tendency for income to be underreported to the Census Bureau.
- The income distribution is highly skewed to the right, meaning that a small proportion of persons account for a large share of income. It is likely that the wealthiest are under-sampled. For example, the maximum income in the PUMS data is $780,960.

The median income values are much closer. This is to be expected since median measures are less affected by extreme values.

Insufficient variation in model predictions of income and underreporting of higher incomes in the PUMS data result in the models under predicting income. This was resolved by adding stochastic variation into the model. Each household prediction is seen as a distribution where the linear model prediction is the mean value of the distribution and a standard deviation for the distribution is calibrated to reproduce the BEA average per capita income.

Figure 3 compares the adjusted and unadjusted model income distributions with the PUMS distribution. The calibrated dispersion factors improve the model fits to the PUMS data, but the fit for Model 1 is not as good as for the other models.

FIGURE 3. COMPARISON OF UNADJUSTED AND ADJUSTED MODEL INCOME DISTRIBUTIONS WITH PUMS DISTRIBUTION



The models were run using the calibrated dispersion factors for all of the validation years (1990, 1995, 2000, 2005, 2010). The inputs for the models included the simulated populations by county and the reported BEA mean or Census median per capita incomes for each county. Figure 4 compares the average per capita incomes for each of the model runs with the BEA targets. Figure 5 compares the modeled median per capita incomes with the Census targets. Models 2 and 3 most closely match the BEA per capita income target. Model 4, which uses county household median income matches least well. However, as might be expected, Model 4 matches the median household income the best.

FIGURE 4. COMPARISON OF MODEL PER CAPITA INCOME WITH BEA MEAN INCOME

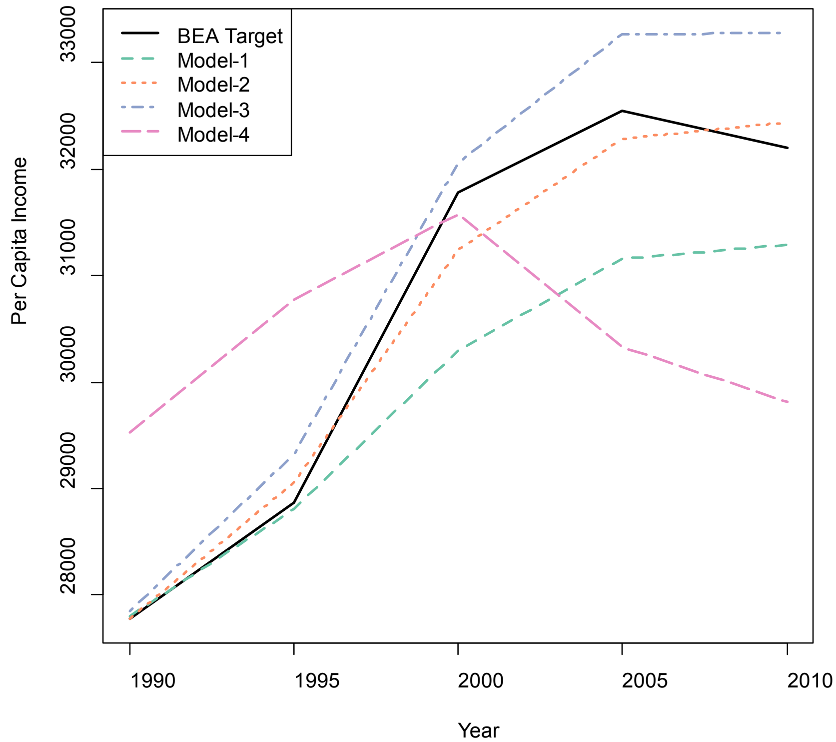
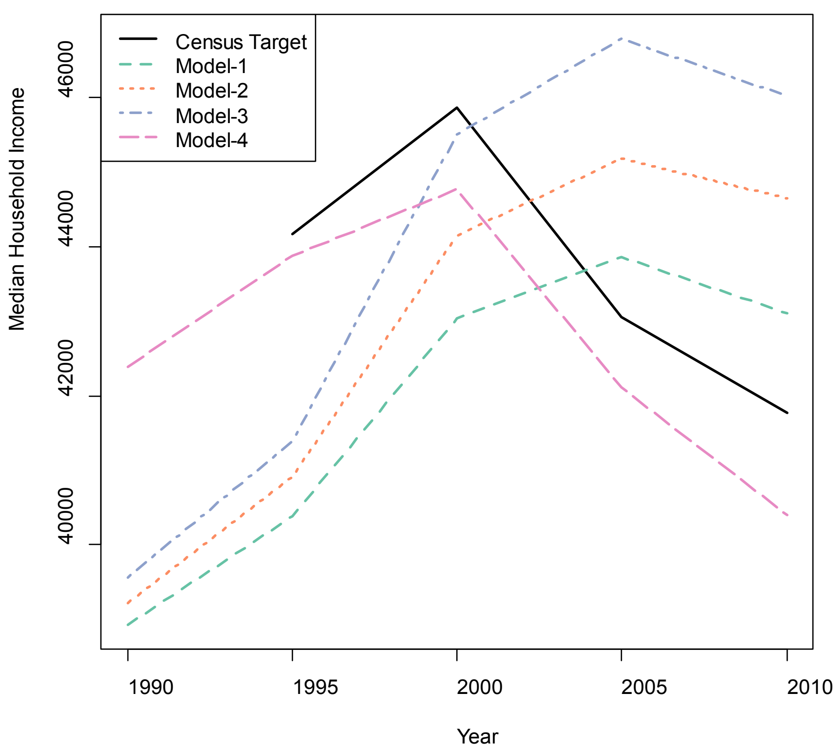


FIGURE 5. COMPARISON OF MODEL PER CAPITA MEDIAN INCOME WITH CENSUS MEDIAN INCOME



Models 2 and 3 match per capita income best, but neither matches the slowing rate of growth from 2000 to 2005 and the decline from 2005 to 2010. It is postulated that changes in the distribution of income over time contribute to the mismatch. To test this hypothesis, dispersion factors were calibrated to match the BEA targets for Model 3 for each test year. Model 3 was chosen over Model 2 because it is more sensible that the effect of persons of different ages on household income should be sensitive to the average per capita income in the area. Figure 6 shows the divergence of the starting value and the calibrated values for each year. It can be seen that except for the year 2000, the dispersion values increase each year.

FIGURE 6. CALIBRATION OF DISPERSION FACTORS BY YEAR

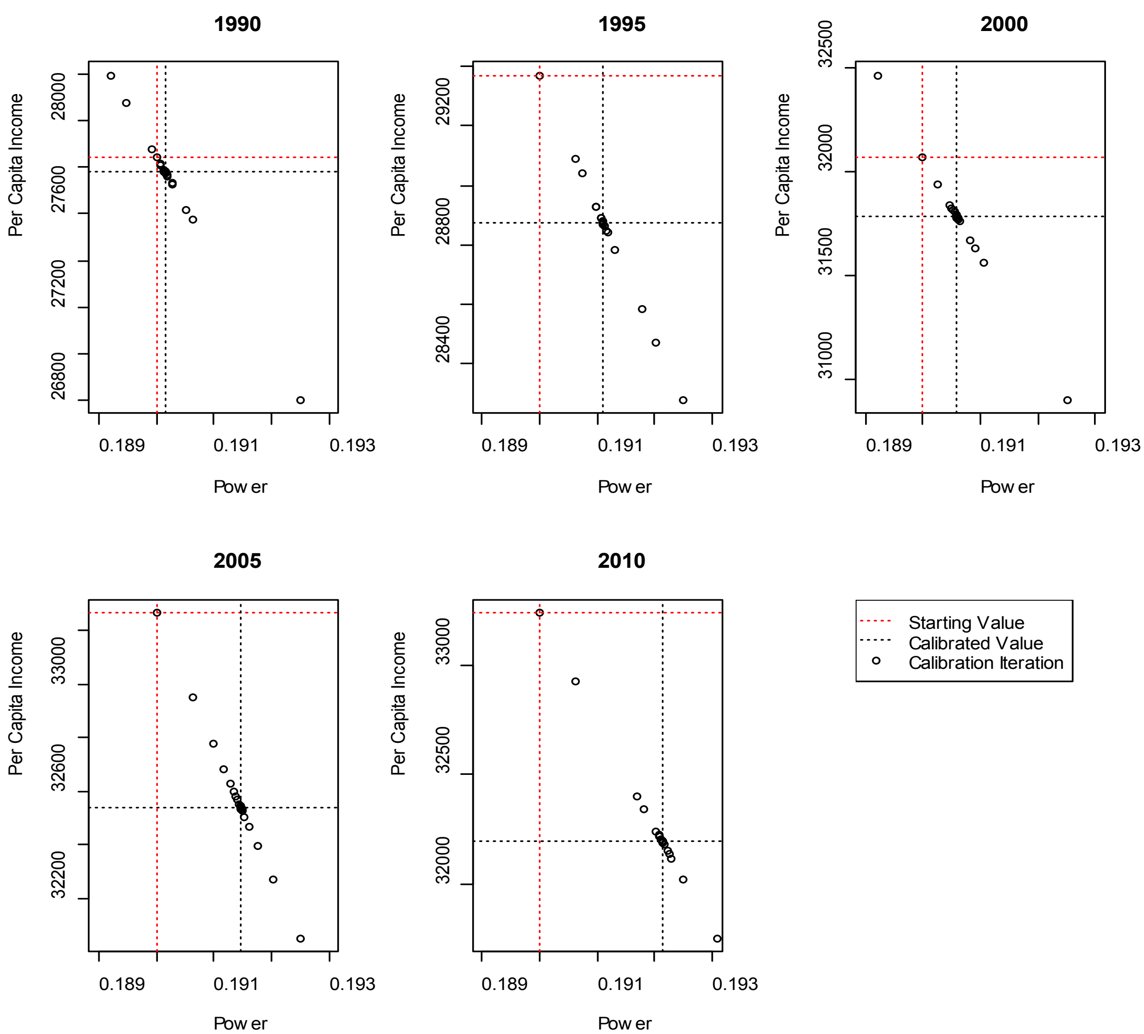
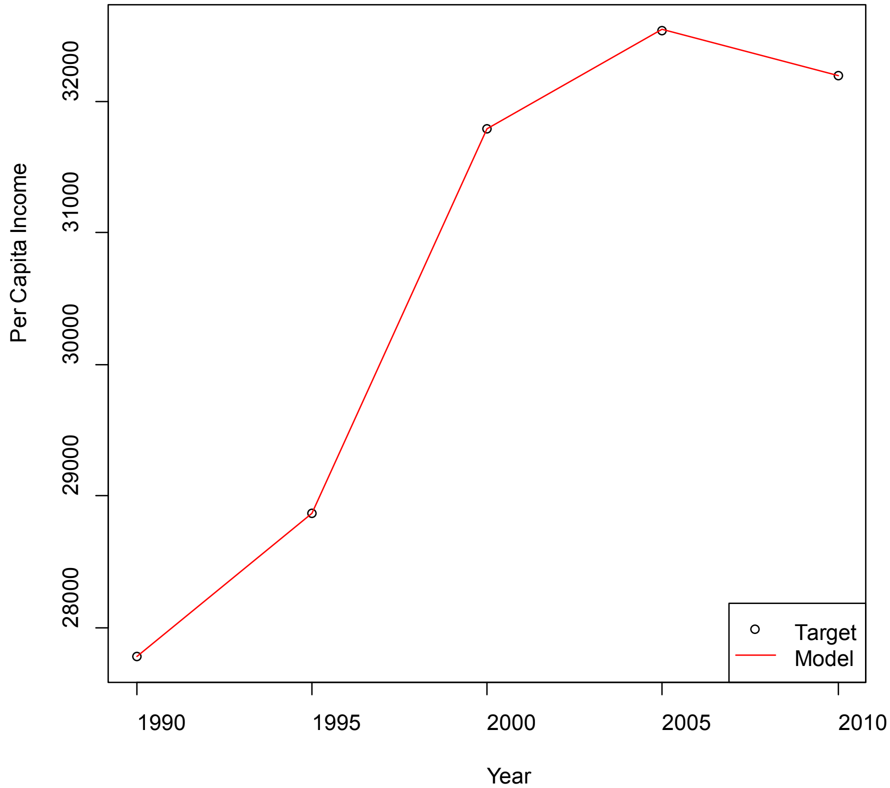


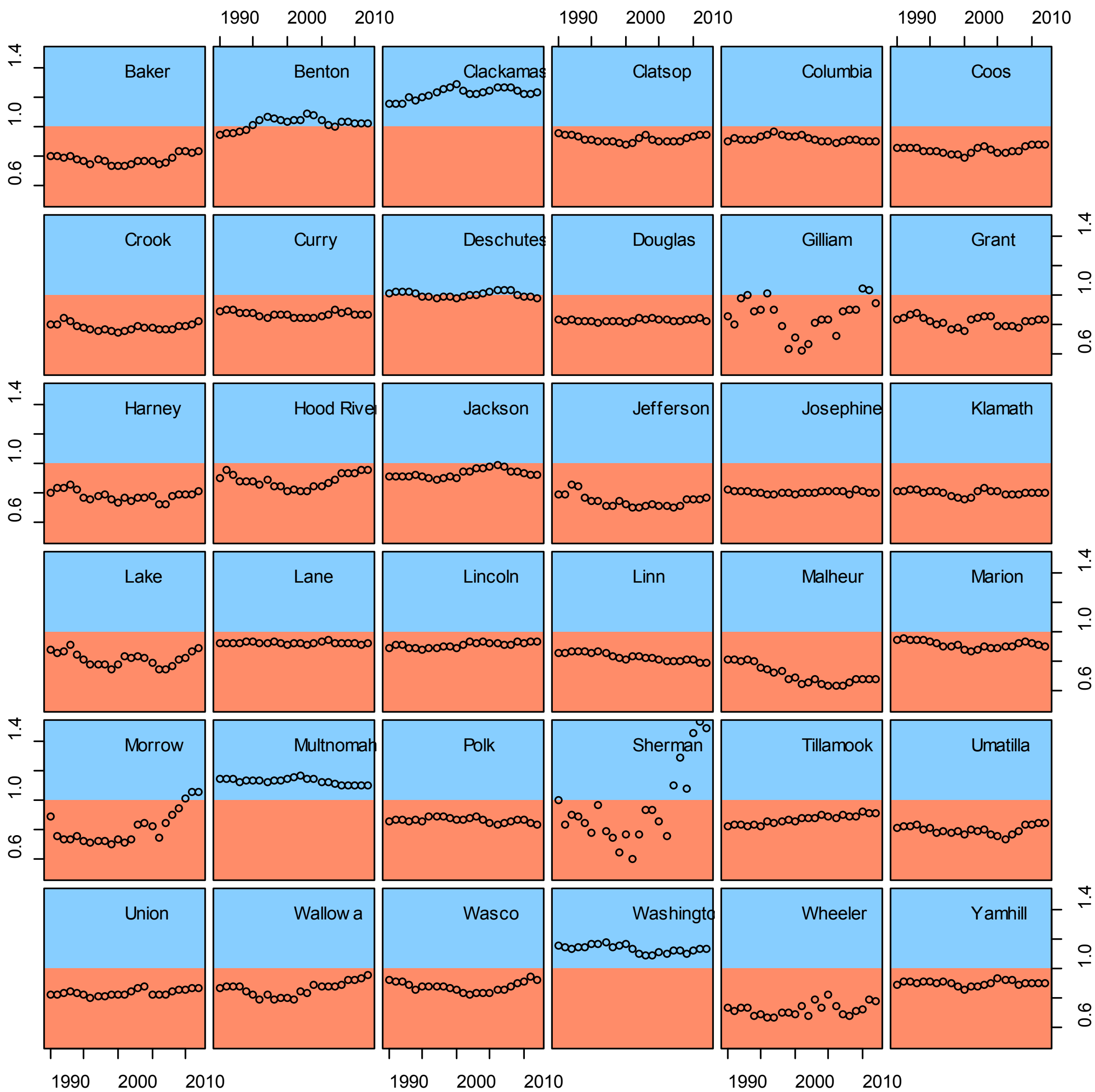
Figure 7 shows that when the calibrated dispersion factors are applied, the model will reproduce the BEA averages. This shows that slight variations in the power transform have significant effects on the average values. The calibrated power transforms are saved for use in further validation. The average power transform for the period is saved for forecasting purposes.

FIGURE 7. COMPARISON OF MODELED PER CAPITA INCOME AND BEA TARGETS USING CALIBRATED DISPERSION FACTORS



The income model predicts household income as a function of the age structure of the household and the average per capita income of the county where the household resides. Figure 8 shows trends in the ratios of county to state average per capita income between 1990 and 2012. With the exception of Benton and Clackamas counties, which gained in their shares of statewide per capita income, the proportions for metropolitan area counties have stayed fairly constant. Larger changes took place for the less populous counties in the state.

FIGURE 8. RATIOS OF COUNTY TO STATEWIDE PER CAPITA INCOME 1990 - 2012



Calculate Population Density and Other Land Use Characteristics

Several land use characteristics must be predicted for households in order to estimate household vehicle ownership and vehicle travel. These include the type of area where the household resides (metropolitan, town, rural), the population density (persons per square mile) of the Census tract where the household resides, and the urban form characteristics of the Census tract where the household resides (urban mixed-use vs. other). Although the vehicle and travel models require Census tract level characteristics, this level of geography is not explicitly represented in the model because GreenSTEP was developed to model GHG mitigation policies at a statewide or metropolitan level. Therefore, models and calculation methods were developed to estimate likely Census tract characteristics for urban areas based on larger scale characteristics. The GreenSTEP and RSPM models take different approaches to model these characteristics.

In GreenSTEP, land use characteristics are assigned to households in the following steps:

1. Each household in each county is assigned to one of three development types - metropolitan, town, or rural. The metropolitan development type includes urbanized portions of a metropolitan statistical area. In Oregon they are the portions of a metropolitan area that are within the metropolitan urban growth boundary. The town development type areas within the urban growth boundaries of incorporated cities that are not within a metropolitan area urban growth boundary and areas within the boundary of an urban unincorporated community that is not within a metropolitan area urban growth boundary. The rural development type includes all other places outside of urban growth boundaries.

2. The geographic extent of urban growth in metropolitan and other urban areas in each county or metropolitan district is calculated.

3. The overall average density for each development type is calculated.

4. Households are assigned a neighborhood population density (i.e. Census tract population density) as a function of the overall metropolitan, town or rural area density where it is located.

5. Households in metropolitan areas are designated as being in an urban mixed-use community/neighborhood or not, based on Census tract density and metropolitan goals for urban mixed-use development.

Households are assigned to metropolitan, town, and rural development types based on 1) the base year distribution of population by development type by county or metropolitan district and, 2) forecasts or assumptions about the proportions of future population growth by type. The base year distribution is developed from Census data, using Census tract population density as an indicator or from metropolitan area household inventories. From these data, the total proportions of households to be assigned to each development type are computed. Households are then randomly assigned to each type using the calculated proportions as probabilities. Since the forecasts of population growth proportions are inputs to the model, they can be modified to test the effects of alternative land use policies on vehicle travel (e.g. what is the effect of a greater proportion of population growth occurring in rural areas).

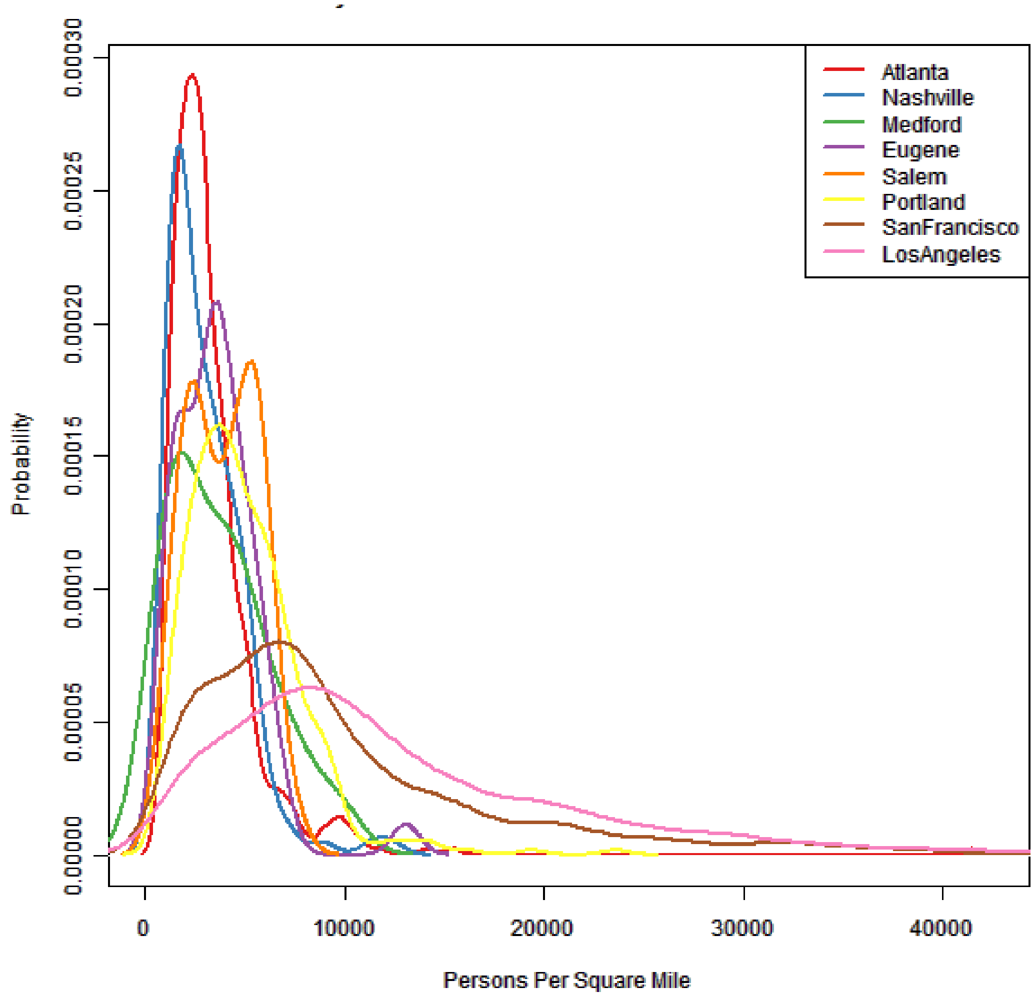
The geographic extent of metropolitan and other urban areas is calculated from base year measurements of urban growth boundary areas by type for each county or metropolitan district and policy inputs which describe how rapidly urban growth boundaries may grow relative to population. For example, a value of 0.5 for metropolitan development means that the urban growth area for the metropolitan area will grow at half the rate of metropolitan population growth.

Households are assigned a neighborhood population density based on the development type that they occupy. A uniform population density is assumed for the rural portions of each county or district. Although densities in rural areas vary, the degree of variation is not large and the variation tends to be localized. For the base year, this density is the household weighted average of rural Census tract densities. This weighting approach is more appropriate than an area-weighted average, which would underestimate average densities because of the large undeveloped areas of public land holdings in most Oregon counties. For forecast years, it is assumed that additional rural population will be added at a density of one household per two acres, since that is the minimum size allowed by state rules for new rural development. The new development is averaged with the base year density to arrive at the forecast rural density.

For metropolitan and town development types, neighborhood population densities are calculated from the overall population density for the area that is urbanized or within an urban growth boundary. The overall population density for one of these types is computed from the number of people assigned to the development type, and the total urban area computed for the type. For households assigned to the town development type, their neighborhood density is the same as the overall average density for the town since small cities tend to be composed of few Census tracts and population densities in small cities tend to be fairly uniform. This is not done for the metropolitan type households.

The assumption of uniform density is not valid for metropolitan areas since Census tract densities can vary by orders of magnitude within a metropolitan area. This can be seen in Figure 9, which compares the Census tract population density distributions of a number of U.S. metropolitan areas.

FIGURE 9. POPULATION DENSITY DISTRIBUTIONS FOR SELECTED METROPOLITAN AREAS



Previous versions of GreenSTEP's census tract density model used the observed census tract density distributions for the Atlanta, Portland, San Francisco and Los Angeles metropolitan areas as prototype sampling distributions. These were supplemented by several additional prototypes having densities less than Atlanta and greater than Los Angeles. The lower density distributions were synthesized by shifting the Atlanta distribution leftward, while the higher density distributions were synthesized by shifting the Los Angeles distribution rightward. The data for each prototype included the overall average metropolitan density and the distribution of Census tract population densities. The density distribution for any given metropolitan area was determined by interpolating between the density distributions of the prototypes whose average densities bound the average density for the subject metropolitan area.

The previous census tract density model had to be replaced because it would not work in and earlier metropolitan version of GreenSTEP (for the Portland metropolitan area) which needed to assign density for subareas of the metropolitan region. The metropolitan prototype approach would not work because district densities have a larger range than metropolitan densities. A scalable approached had to be developed instead.

The procedure for developing the new model again used the census tract level population and density information for the prototype metropolitan areas (Portland, Los Angeles, San Francisco, and Atlanta). Census tracts having population densities less than 1000 persons per square mile were dropped from the estimation data set as being unrepresentative of urbanized areas. Census tract densities were normalized by computing the natural log of population density for each tract in an urbanized area and dividing by the natural log of the population weighted average density for the urbanized area. Figure 10 shows the probability distributions of normalized census tract population densities for the four metropolitan areas (histograms) and compares those distributions to normal distributions using the mean and standard deviation values of the observed distributions (dashed red lines).

The graphs in Figure 10 show that the distributions of normalized census tract densities are reasonably well approximated by the normal distributions. Table 8 compares the means and standard deviations for these four metropolitan areas and for the 3 mid-sized metropolitan areas in Oregon (Medford, Salem, Eugene). It can be seen that the mean and standard deviation values are all fairly similar to one another. There is less variation among the Oregon metropolitan means and standard deviations. This similarity of normalized distributions suggests a scalable approach to estimating a reasonable distribution of census tract densities for urban areas of different sizes or portions of urban areas. Based on these results, parameter values of 1.02 and 0.07 were chosen for use in the latest statewide and metropolitan area models.

FIGURE 10. COMPARISON OF NORMALIZED POPULATION DENSITY DISTRIBUTIONS FOR THE PORTLAND, ATLANTA, SAN FRANCISCO, AND LOS ANGELES METROPOLITAN AREAS

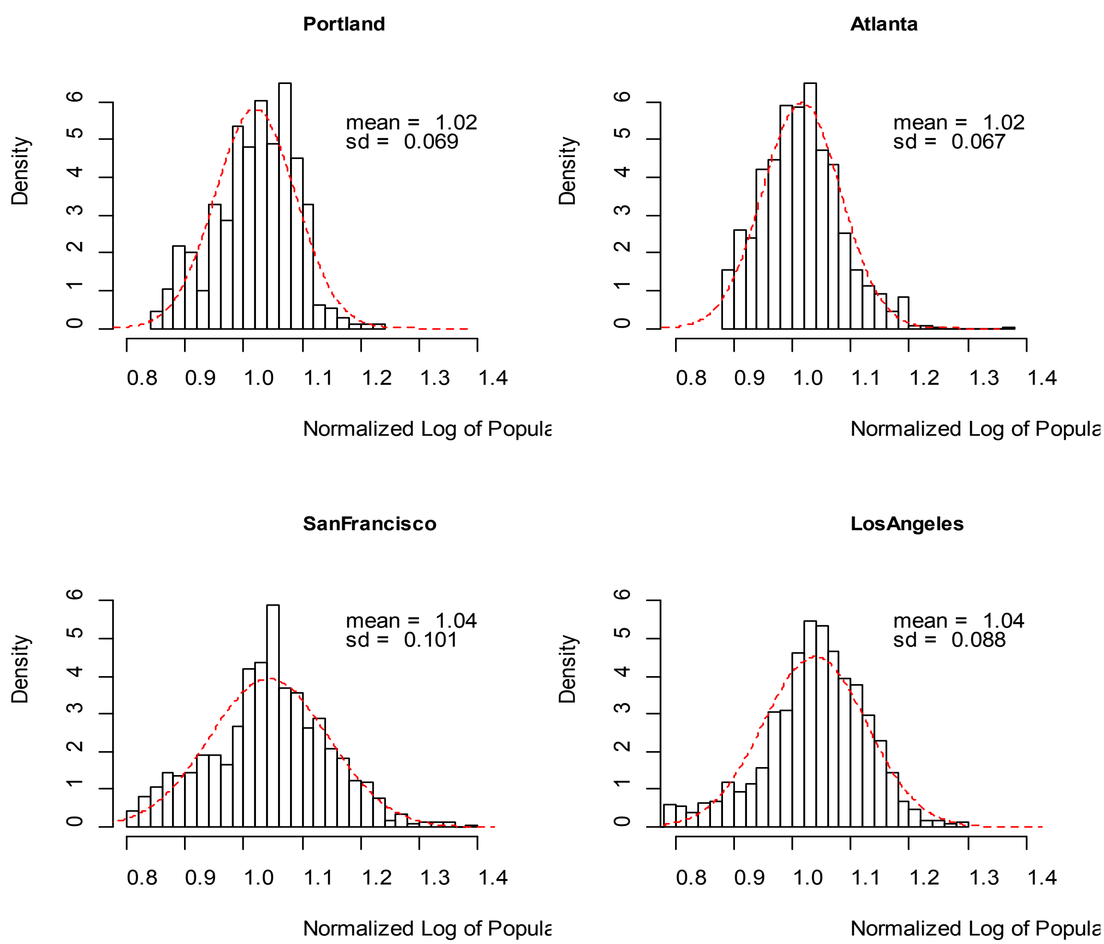


TABLE 8. MEANS AND STANDARD DEVIATION OF NORMALIZED CENSUS TRACT POPULATION DENSITIES FOR SELECTED METROPOLITAN AREAS

Place	Mean	SD
Medford	1.029	0.0882
Salem	1.017	0.0633
Eugene	1.020	0.0714
Portland	1.020	0.0686
Atlanta	1.016	0.0668
San Francisco	1.043	0.1013
Los Angeles	1.039	0.0881

The density model in GreenSTEP to calculate the population density distribution for a metropolitan area or a district within a metropolitan area is as follows:

$$D = \exp(N(\mu, \delta^2) * \log(WtAveDen))$$

where:

$N(\mu, \delta^2)$ is a normal distribution having mean and standard deviation of the estimated values of 1.02 and 0.07 respectively from which 1 million samples are drawn.

$WtAveDen$ is the population weighted average density for the metropolitan area or district within the metropolitan area.

Since the population weighted average density is not a known quantity, but the overall average density is, the population weighted average density must be approximated. This can be done because *D* is continuous and average density can be calculated from *D* as follows:

$$\frac{n}{\sum_{i}^{n} \frac{1}{d_i}}$$

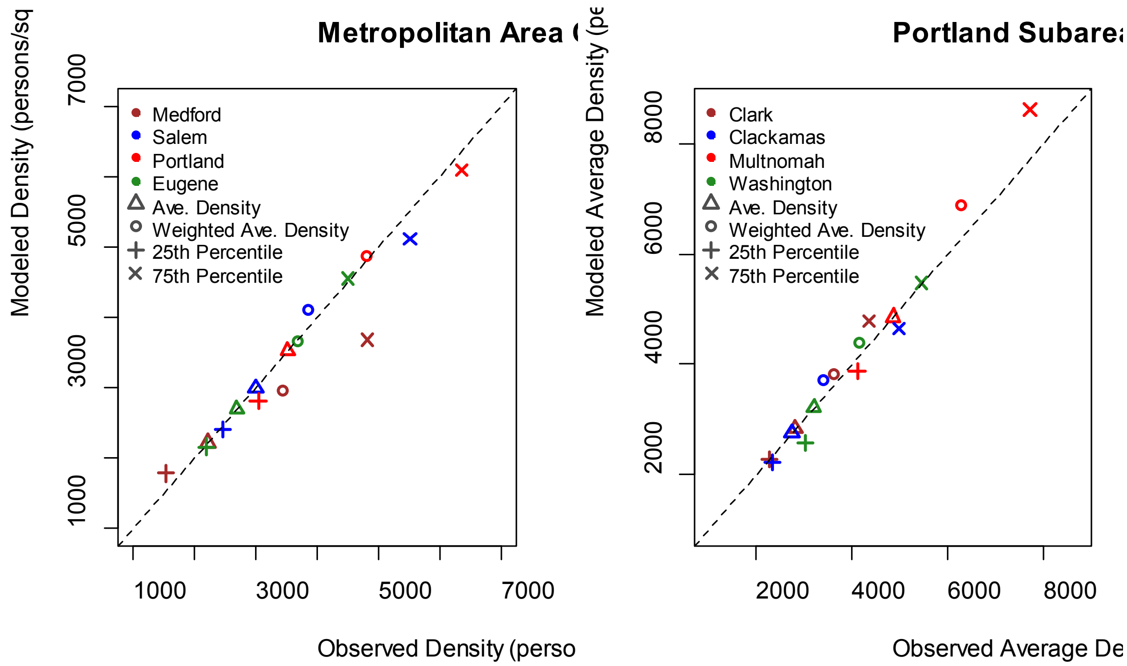
where:
n is the number of samples
d_i is density of each sample

The model uses a binary search algorithm to find a value for the population weighted average density which produces a density distribution whose average density is within 0.1% of the input value.

The scalability of this approach was tested by applying the model to the 4 larger metropolitan areas in Oregon (Portland, Salem, Eugene, Medford) and by applying the model to subareas of the Portland metropolitan area. The Portland subareas were defined by partitioning the census tract dataset by county (Clark, Clackamas, Multnomah, Washington). Figure 11 shows the results for the metropolitan area test in the left-hand graph. The right-hand graph shows the results for the metropolitan subarea test.

The overall average density values are shown by the triangular marks. These all fall on the diagonal line, showing that observed and estimated values are the same, because the model algorithm is designed to match these values. The population weighted average values are shown by the circular marks. These provide an indication of the overall fits of the modeled density distributions to the observed distributions. These are fairly close to the diagonal line for both tests. The vertical cross marks show the 25th percentile density values. These too are close to the diagonal lines. Finally, the angled cross marks show the 75th percentile density values. As might be expected, because the population density distribution has a long right-hand tail, some of these marks depart more from the diagonal line. The model underestimates the 75th percentile census tract density for the Medford metropolitan area and overestimates the 75th percentile census tract density for the Multnomah County subarea. Overall, the modeled distributions do a reasonable job of simulating the observed distributions at different scales.

FIGURE 11. COMPARISON OF OBSERVED AND MODELED DENSITIES FOR METROPOLITAN AREAS AND FOR METROPOLITAN SUBAREAS



The current GreenSTEP model assigns households within a County or metropolitan district randomly to development types and to neighborhood densities.

The RSPM model uses a different method to calculate density because it uses a more detailed geographic representation of the metropolitan area. As shown in Figure 2, the metropolitan area is split into divisions and those divisions are split into districts in turn. Households are simulated at the division level. Those households are then assigned to districts within the division. Districts are census tracts or geographic areas that are approximately the size of census tracts. The density assigned to each household is simply the sum of all persons of households assigned to the district where the household is assigned, divided by the area of the district (not counting large undevelopable acreage such as rivers and preserved open space).

The RSPM assigns households to districts using a housing type model. An estimate or forecast of housing types (e.g. single family detached, multi-family, etc.) by district is an input to the model. A housing choice model is used to assign households in each division to housing types. This model, as described below, responds to the supply of housing of each type and to household characteristics. After all simulated households in a metropolitan division have been assigned to a housing type, they are then assigned to a district within the division based on the supply of housing by type in each district and an attraction weight that is calibrated for the base year so that the average per capita income of the households assigned to each district is similar to the Census average. Households are assigned to districts in descending order of household income.

The RSPM housing type model uses a sequential binary logit model to assign households to housing types. The sequence of choices is shown in Figure 12. The model may be run with only two housing types, single family detached vs. multifamily, or with a more disaggregate set of housing types. At each sequential step, the constants of the model are adjusted so that the proportions of households assigned to each type match the proportions of housing available. For the simpler housing type model, only the first step shown in Figure 12 (Model 1) is carried out. In the more complex model, three other models are applied to complete the assignment. The specifications and estimation statistics for the four models are shown in Tables 9 through 12. The independent variables for these models are household income, household size, and age of household head.

FIGURE 12. HOUSING TYPE LOGIT MODEL STRUCTURE

```
              Single family or Multifamily (Model 1)
                 /                          \
        SFD or MH (Model 2)          A5P or SFA/A24 (Model 3)
          /      \                      /         \
       SFD      MH                  A5P    A24 or SFA (Model 4)
                                               /        \
                                            A24       SFA
```

Building type: SFD = single family detached; SFA = single family attached;
A24 = Duplex/Triplex/Quadplex; A5p = Apartments;
MH = mobile home

TABLE 9. ESTIMATION RESULTS FOR HOUSING TYPE MODEL 1

```
glm(formula = Choice ~ AgeOfHead + Income + HhSize + AgeOfHead:Income,
    family = binomial, data = Data..)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.5379   0.1047   0.4240   0.6404   2.0211

Coefficients:
                   Estimate  Std. Error z value  Pr(>|z|)
(Intercept)       -3.686e+00   2.443e-01 -15.087   < 2e-16 ***
AgeOfHead          3.905e-01   2.808e-02  13.906   < 2e-16 ***
Income             4.113e-05   5.501e-06   7.476  7.63e-14 ***
HhSize             5.011e-01   4.436e-02  11.295   < 2e-16 ***
AgeOfHead:Income  -2.251e-06   6.995e-07  -3.218   0.00129 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 4735.7  on 4486  degrees of freedom
Residual deviance: 3620.8  on 4482  degrees of freedom
AIC: 3630.8

Number of Fisher Scoring iterations: 6
```

TABLE 10. ESTIMATION RESULTS FOR HOUSING TYPE MODEL 2

```
glm(formula = Choice ~ AgeOfHead + Income, family = binomial,
    data = DataSF..)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.7668   0.3064   0.4748   0.6224   0.8919

Coefficients:
                Estimate  Std. Error  z value     Pr(>|z|)
(Intercept)     1.662e+00   2.322e-01    7.156     8.30e-13 ***
AgeOfHead      -9.707e-02   2.494e-02   -3.892     9.96e-05 ***
Income          1.824e-05   1.705e-06   10.702      < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 2841.1  on 3496  degrees of freedom
Residual deviance: 2650.9  on 3494  degrees of freedom
AIC: 2656.9

Number of Fisher Scoring iterations: 6
```

TABLE 11. ESTIMATION RESULTS FOR HOUSING TYPE MODEL 3

```
glm(formula = Choice ~ Income + HhSize + HhSize:AgeOfHead, family =
binomial, data = DataMF..)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5166  -1.1817   0.8666   1.0613   2.3579

Coefficients:
                   Estimate  Std. Error  z value   Pr(>|z|)
(Intercept)       1.066e+00   1.509e-01    7.068   1.57e-12 ***
Income           -5.257e-06   2.647e-06   -1.986   0.047079 *
HhSize           -2.281e-01   8.659e-02   -2.635   0.008425 **
HhSize:AgeOfHead -4.938e-02   1.282e-02   -3.851   0.000118 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1372.4  on 989  degrees of freedom
Residual deviance: 1296.1  on 986  degrees of freedom
AIC: 1304.1

Number of Fisher Scoring iterations: 3
```

TABLE 12. ESTIMATION RESULTS FOR HOUSING TYPE MODEL 4

```
glm(formula = Choice ~ HhSize + AgeOfHead + Income + HhSize:AgeOfHead,
    family = binomial, data = DataAPT..)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7991  -1.2023   0.7394   1.0911   1.7076

Coefficients:
                   Estimate  Std. Error z value   Pr(>|z|)
(Intercept)       2.413e+00   5.413e-01   4.457   8.3e-06 ***
HhSize           -7.173e-01   2.224e-01  -3.225   0.00126 **
AgeOfHead        -2.128e-01   7.259e-02  -2.931   0.00338 **
Income           -1.006e-05   3.827e-06  -2.630   0.00854 **
HhSize:AgeOfHead  7.441e-02   3.350e-02   2.221   0.02633 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 681.25  on 493  degrees of freedom
Residual deviance: 650.72  on 489  degrees of freedom
AIC: 660.72

Number of Fisher Scoring iterations: 4
```

When the housing type model is run, the constants for each logit model are adjusted so that the proportions of households assigned to each housing type match the input proportions. Which households are assigned what types of housing varies depending on the relative proportions of types that are available. A sensitivity test was carried out to evaluate how changing housing type proportions affects the characteristics of household assigned to the types. Sensitivity tests were performed to evaluate how the model responds to changes in the supply of housing. Table 13 shows two housing supply scenarios that are specified in terms of the proportions of each housing type. Table 14 shows the corresponding logit model constants calculated by the model to match housing choices to the available supply.

TABLE 13. TEST HOUSING SUPPLY SCENARIOS

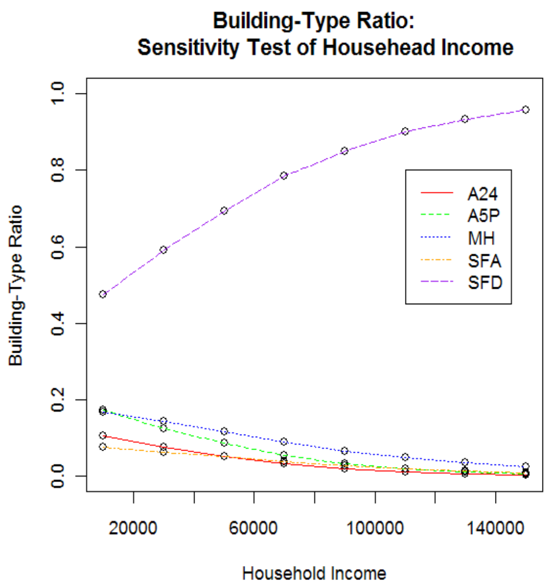
	A24	A5P	SFA	SFD	MH
Scenario 1 Proportions	0.06	0.11	0.05	0.67	0.11
Scenario 2 Proportions	0.13	0.30	0.03	0.44	0.10

TABLE 14. CALCULATED LOGIT MODEL CONSTANTS FOR TEST SCENARIOS

	Model 1	Model 2	Model 3	Model 4
Scenario 1 Constants	-3.685988	1.661680	1.0662196	2.412599
Scenario 2 Constants	-1.507568	-0.474548	0.8594512	1.547241

Figures 13, 14, and 15 compare the two scenarios with respect to how housing type proportions vary by household income, household size, and age of household head. The sensitivities appear to be sensible. It can be seen in Figure 13 that constraining the supply of single family detached housing (Scenario 2, right hand chart) has a greater effect on the choice of lower income households than higher income households. Figure 14 shows that smaller households are affected more than larger households. Finally, Figure 15 shows that younger households are affected more than older households, although the difference is not as pronounced as with income and household size.

FIGURE 13. COMPARISON OF VARIATION IN HOUSING TYPE PROPORTIONS WITH HOUSEHOLD INCOME. SCENARIO 1 ON LEFT AND SCENARIO 2 ON RIGHT.



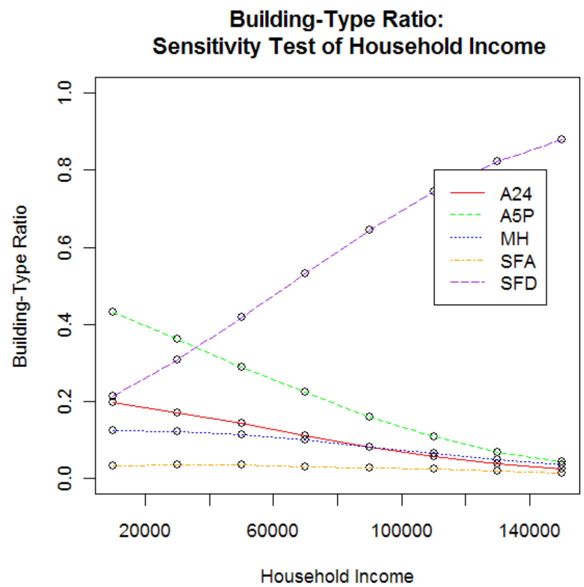
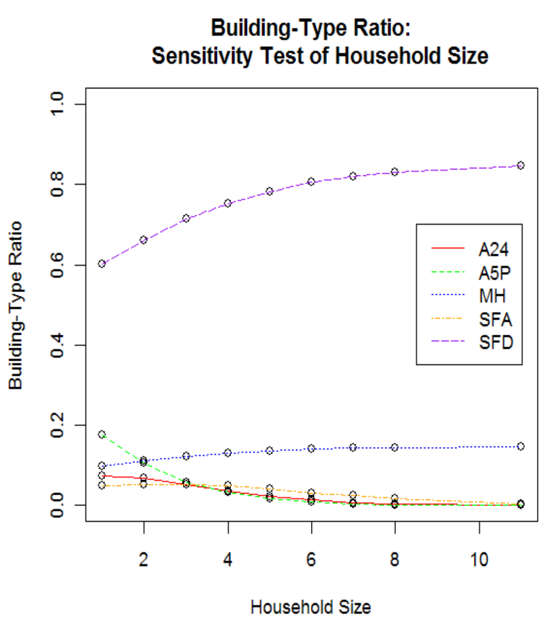


FIGURE 14. COMPARISON OF VARIATION IN HOUSING TYPE PROPORTIONS WITH HOUSEHOLD SIZE. SCENARIO 1 ON LEFT AND SCENARIO 2 ON RIGHT.



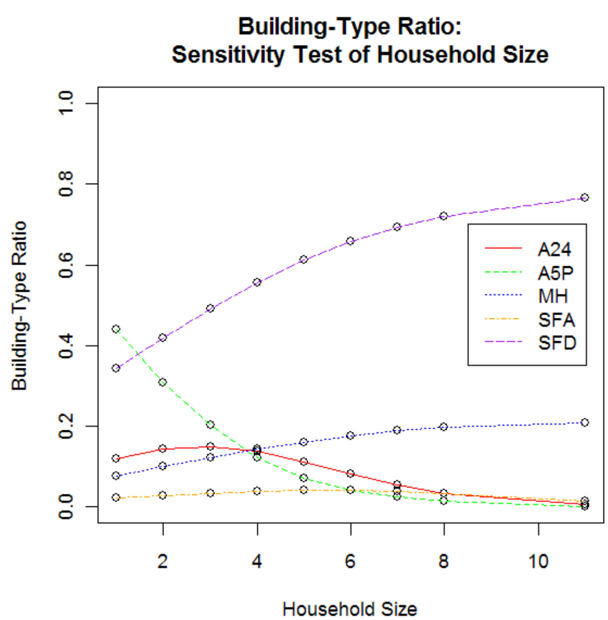
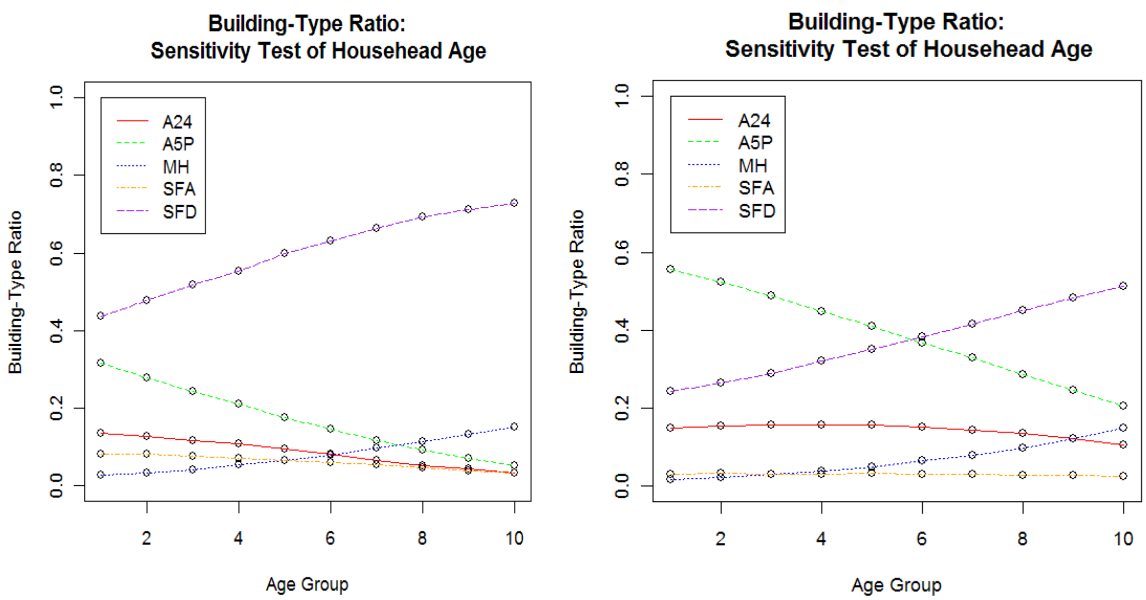


FIGURE 15. COMPARISON OF VARIATION IN HOUSING TYPE PROPORTIONS WITH HOUSEHOLD SIZE. SCENARIO 1 ON LEFT AND SCENARIO 2 ON RIGHT.



After the simulated households in each division are assigned a housing type, they are assigned to districts based on their assigned housing type, the supply of housing of their type in each district, and a district weight that is calibrated so that district income averages match Census averages. Households are assigned by housing type with single family detached households being assigned last. Households are assigned in descending order of income. Once all households have been assigned to districts, the population density of each district is calculated and the value calculated for each district is assigned to households located in the district.

Density is one of several land use variables associated with the amount of vehicle travel that occurs. These are often referred to as the 4-Ds or 5-Ds. Following are the variables included in the Transportation Research Board (TRB) Special Report 298:

- *Density*: Population and employment by geographic unit (e.g., per square mile, per developed acre).
- *Diversity*: Mix of land uses, typically residential and commercial development, and the degree to which they are balanced in an area (e.g., jobs-housing balance).
- *Design*: Neighborhood layout and street characteristics, particularly connectivity, presence of sidewalks and other design features (e.g., shade, scenery, presence of attractive homes and stores) that enhance the pedestrian and bicycle friendliness of an area.
- *Destination accessibility*: Ease or convenience of trip destinations from point of origin, often measured at the zonal level in terms of distance from the central business district or other major centers.

- *Distance to transit*: Ease of access to transit from home or work (e.g., bus or rail stop within 1/4–1/2 mi of trip origin).

Several land-use related variables in the NHTS dataset were tested in the vehicle ownership and vehicle travel models to capture these effects. Census tract population density (HTPPOPDN) was found to be highly significant. Household and worker density measures are also available, but population density was found to have a stronger association.

Density measures are available at the Census block group level and the Census tract level. The Census tract level measure is used because it is in keeping with the large scale nature of the GreenSTEP model and is more likely to provide a more consistent indicator of transportation effects related to population density.

The other variable found to be highly significant in these models is the HTHUR variable. This variable is explained in Appendix Q of the NHTS User's Guide, and was developed by Claritas, Inc., to represent the rural urban continuum.[2] Census tracts are identified as being rural, town, suburban, second city, or urban. Rural and town designations are based on the population density of the area where the Census tract is located. The suburban, second city and urban designations are based on the combination of the population density at their location and the population density at the location of the nearest population center.

The urban classification, according to the classification system represented by the HTHUR variable, is likely to represent several land use characteristics on the TRB list. The urban classification is closely related to the older, more central portions of metropolitan areas. These areas typically have more neighborhood-level mixing of different land uses, a grid-based street system with greater connectivity, greater pedestrian accessibility and sidewalk orientation of land uses, and greater transit accessibility. Since the variable measures the relationship of the Census tract to the density of the nearest population center, it also has a relationship to the destination accessibility of the area. The urban classification is useful for capturing land use effects in the vehicle ownership and vehicle travel models that are not captured by population density alone.

Although the HTHUR variable is clearly related to population density, the relationship is not so strong as to create co-linearity problems in the models that use both variables. Table 15 shows that almost all of the households at densities of 30,000 persons per square mile are identified as being in an urban type area. Almost none of the households located in densities less than 3,000 persons per square mile are identified as being in an urban type area. However, in the middle range of densities, at which about two-thirds of the "urban mixed-use" households live, there is a substantial amount of variation in the percentage of households of this type. Table 16 shows that the residual deviance of a binary logit model to predict urban mixed-use type based on population density is relatively high.

---

[2] 2001 National Household Travel Survey. *User's Guide,* p. Q3.

Miller, David R., Ken Hodges. *A Population Density Approach to Incorporating an Urban-Rural Dimension into Small Area Lifestyle Clusters*

TABLE 15. COMPARISON OF POPULATION DENSITY AND "URBAN" TYPE OF HOUSEHOLDS

Population Density	Urban Type Percentage of Households	Percentage of Urban Type Households	Total Number of Households
50	0	0	9653
300	0.1	0.2	10079
750	0.3	0.3	4971
1500	0.8	1.0	6639
3000	3.9	6.6	9754
7000	19.9	32.5	9399
17000	67.8	33.0	2809
30000	95.5	26.4	1592

Although the "urban" type is not determined solely by the population density of the Census, it is important to account for the fact that Census tracts having higher population densities are more likely to be an "urban" type. Not accounting for this relationship will result in an underestimation of the effect on household vehicle travel of land use policies that result in higher densities. A simple binomial logit model was developed to predict the likelihood that a household is located in an "urban" type area based on Census tract population density. Table 16 shows a summary of the model.

TABLE 16. URBAN MIXED-USE DEVELOPMENT TYPE MODEL

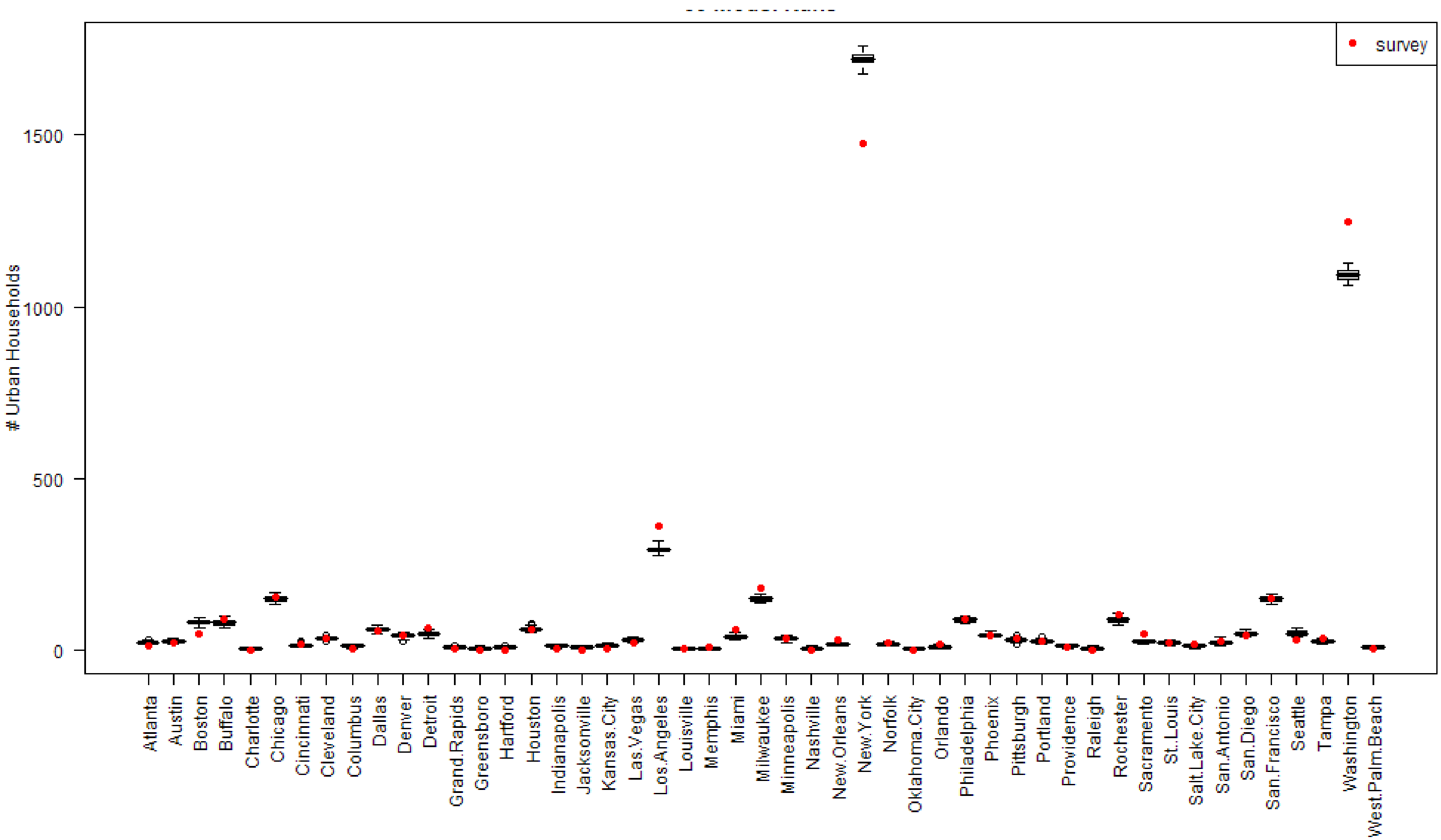
```
glm(formula = Urban ~ Htppopdn, family = binomial, data = TestHh..)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.2416  -0.4326  -0.3533   0.1024   2.5263
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.163e+00  3.932e-02  -80.44   <2e-16 ***
Htppopdn     2.804e-04  4.482e-06   62.55   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 21150  on 18428  degrees of freedom
Residual deviance: 11972  on 18427  degrees of freedom
AIC: 11976

Number of Fisher Scoring iterations: 5
```

Figure 16 compares observed and modeled values by metropolitan area for the NHTS survey dataset. The box and whiskers plots show the distributions of results for 30 model runs. The red dots show the survey results.

FIGURE 16. OBSERVED AND ESTIMATED NUMBER OF URBAN HOUSEHOLDS BY METROPOLITAN AREA



The amount of urban mixed-use development is also affected by land use policies and the model enables users to input a target urban mixed-use proportion for each metropolitan area (GreenSTEP) or each metropolitan district (RSPM). When a target is provided, the model adjusts the intercept shown in Table 16 so that the model matches the target. Not all possible targets are achievable, however. For example, it is unrealistic to expect a high percentage of urban mixed-use development in a low population density area. Table 17 shows the results of a sequence of tests where the model attempts to match the targets. Rows correspond to population densities and columns to target values. Table cells shaded yellow are within 0.01 of the target values. In most cases, the model can be adjusted to achieve the target proportion, but high proportions are not achievable at lower densities and a minimum proportion can be expected at all densities.

TABLE 17. TEST OF URBAN MIXED-USE TARGET SETTING

	0.05	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**	**0.55**	**0.6**	**0.65**	**0.7**	**0.75**	**0.8**	**0.85**	**0.9**	**0.95**	**1**
1000	0.201	0.201	0.201	0.201	0.251	0.303	0.351	0.402	0.453	0.504	0.548	0.594	0.644	0.606	0.555	0.505	0.555	0.503	0.504	0.505
2000	0.202	0.202	0.202	0.202	0.251	0.302	0.351	0.402	0.453	0.504	0.550	0.594	0.644	0.605	0.555	0.504	0.555	0.503	0.504	0.555
3000	0.101	0.101	0.202	0.198	0.252	0.302	0.350	0.402	0.453	0.503	0.555	0.595	0.644	0.693	0.707	0.656	0.605	0.555	0.503	0.503
4000	0.202	0.202	0.202	0.198	0.248	0.298	0.351	0.400	0.453	0.505	0.554	0.596	0.644	0.693	0.743	0.757	0.798	0.798	0.798	0.798
5000	0.198	0.198	0.198	0.198	0.248	0.301	0.347	0.400	0.453	0.499	0.547	0.595	0.645	0.693	0.743	0.792	0.842	0.851	0.851	0.851
6000	0.202	0.202	0.202	0.202	0.248	0.298	0.348	0.397	0.450	0.495	0.545	0.594	0.646	0.695	0.744	0.793	0.842	0.858	0.808	0.757
7000	0.248	0.248	0.248	0.248	0.248	0.302	0.352	0.402	0.450	0.501	0.548	0.597	0.646	0.693	0.744	0.793	0.842	0.891	0.905	0.905
8000	0.248	0.248	0.248	0.248	0.248	0.303	0.353	0.402	0.449	0.500	0.551	0.597	0.645	0.695	0.744	0.793	0.842	0.891	0.858	0.807
9000	0.248	0.248	0.248	0.248	0.252	0.303	0.352	0.404	0.448	0.500	0.552	0.602	0.644	0.695	0.744	0.793	0.842	0.891	0.909	0.858
10000	0.248	0.248	0.248	0.248	0.248	0.297	0.352	0.402	0.446	0.501	0.555	0.605	0.650	0.694	0.744	0.793	0.843	0.892	0.909	0.941

Calculate Metropolitan Freeway, Arterial and Public Transit Supply Levels

Metropolitan area freeway, arterial and public transit supply levels are important inputs to the household vehicle ownership and travel models and to fuel efficiency models. The metropolitan area freeway supply (lane-miles per capita) and transit supply (annual revenue miles per capita) are significant predictors of metropolitan household vehicle ownership and travel. Arterial supply (lane-miles per capita) is not a significant predictor of vehicle ownership or travel, but along with freeway supply, is important for estimating the traffic congestion levels. Traffic congestion affects average trip speeds, vehicle fuel economy, and emissions.

The calculations of future freeway, arterial and transit supplies are straight forward. The model data include year 2000 inventories of freeway lane-miles, arterial lane-miles and transit revenue-miles by metropolitan area. Transit revenue miles are expressed in bus equivalents (passenger miles per revenue mile). The method for calculating changes in future lane miles has been modified. In earlier versions, the change in lane miles was expressed as an elasticity with respect to the change in population. In this version, future lane miles are expressed as a ratio with respect to base year lane miles. For example a value of 1.2 for freeways in the year 2050 would mean that the number of freeway lane miles in 2050 would be 1.2 times the number of freeway lane miles in the base year. The same approach is used for specifying the growth in transit revenue miles.

The user must also input the assumed portion of public transit supply that will be rail (e.g. light rail or trolley). In previous versions, this is used to compute the amounts of fuels vs. electric power used to provide future public transit service. This has been changed in version 3.5. The portion of transit revenue miles powered by electricity is specified in the transit fuels inputs.

Determine Households Affected by Travel Demand Management and/or Vehicle Operations and Maintenance Programs

Employee Commute Options Programs and Individualized Marketing Programs

Employee commute options (ECO) programs are work-based travel demand management programs. They may include transportation coordinators, employer-subsidized transit passes, bicycle parking, showers for bicycle commuters, education and promotion, carpool and vanpool programs, etc. Individualized marketing (IM) programs are travel demand management programs focused on individual households. IM programs involve individualized outreach to households that identify household travel needs and ways to meet those needs with less vehicle travel.

Monte Carlo processes are used to identify which households participate in ECO programs and which participate in IM programs. The proportion of employees participating in ECO programs is a policy input. This is converted into a proportion of working age persons using an assumed labor force participation rate (0.65) that is used to sample working age persons in households.

The sampling procedure for IM programs is more complicated because IM programs work best in neighborhoods where a number of travel options are available. In addition to the overall input assumption for the percentage of households participating in an IM program, assumptions are made about the minimum population density necessary to implement a successful IM program and whether an urban mixed-use urban form is necessary. The default parameters are a density threshold of 4,000 persons per square mile and the requirement for an urban mixed-use urban form. The number of households identified as participating is the minimum of the number needed to meet the program goal or the number of qualifying households (based on density and urban mixed-use requirements).

Eco-Driving

Eco-driving involves educating motorists on how to drive in order to reduce fuel consumption and cut emissions. Examples of eco-driving practices include avoiding rapid starts and stops, matching driving speeds to synchronized traffic signals, and avoiding idling. Practicing eco-driving also involves keeping vehicles maintained in a way that reduces fuel consumption such as keeping tires properly inflated and reducing aerodynamic drag. For the purposes of the GreenSTEP and RSPM models, fuel economy benefits of improved vehicle maintenance are included in the eco-driving benefit.

The effect of eco-driving programs is modeled by identifying participating households based on a policy assumption about the proportion of participating households. A Monte Carlo process is used to designate households. The average fuel economy of the vehicles of participating households is increased by an average rate of by specifying as an input, the proportion of households that will be participants. This proportion is used in a Monte Carlo process to assign individual households as participants. The fuel economy of all household vehicles of participating households is increased by a factor representing the average fuel economy gains of persons who are trained in eco-driving techniques. A default 19% improvement in vehicle fuel economy is assumed based on information in the "Moving Cooler" study.[3]

Low Rolling Resistance Tires

Low rolling resistance tires reduce fuel consumption by reducing energy losses due to tire deformation as the tire rolls down the road. The effect of low rolling resistance tires is modeled by specifying the proportion of households that use low rolling resistance tires. Households are

[3] Cambridge Systematics, "Moving Cooler", Urban Land Institute, Washington, D.C., 2009, Technical Appendix, Table 7.1, page B-63.

designated using a Monte Carlo process. The fuel economy of vehicles in these households is assumed to increase by 1.5%.[4]

Calculate Vehicle Ownership and Adjust for Carsharing

The vehicle ownership model predicts the number of vehicles owned by each household. It is implemented in two stages. In the first stage, households are categorized by the ratio of vehicles per driving age person according to the following categories:

1. Zero vehicles.
2. Less than one vehicle per driving age person.
3. One vehicle per driving age person.
4. More than one vehicle per driving age person.

In the second stage, the number of vehicles for category 2 and category 4 households is determined.

The first stage is implemented using a set of binomial logit models. Separate sets of models are used for metropolitan and non-metropolitan areas. The metropolitan models include freeway supply, transit supply and urban type variables, while the non-metropolitan models do not.

The models are segmented into three groups defined by the number of persons of driving age in the household: one driving age person, two driving age persons, three or more driving age persons. Tables 18, 19, 20 and 21 show the statistics for models for the metropolitan zero vehicles, less than one vehicle, one vehicle, and greater than one vehicle households, respectively. Colons between variable names indicate that the variables are interacted. The variables in the models have the following meanings:

- Hhincttl – total annual household income in dollars
- Htppopdn – census tract population density in persons per square mile
- Transmilescap – annual metropolitan transit revenue miles per person
- Urban – dummy variable indicating whether household is in an urban mixed-use area
- Fwylnmicap – metropolitan freeway lane miles per 1000 persons
- OnlyElderly – dummy variable indicating whether all persons in the household are 65 years old or older

[4] Transportation Research Board, "Tires and Passenger Vehicle Fuel Economy", Special Report 286, Transportation Research Board, Washington, D.C., 2006.

TABLE 18. METROPOLITAN AREA ZERO-VEHICLE HOUSEHOLD MODELS

```
One Driving Age Person in Household
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)             -6.831e-01  2.439e-01  -2.800 0.005108 **
Hhincttl                -1.104e-04  8.844e-06 -12.484  < 2e-16 ***
Htppopdn                 1.095e-04  3.998e-05   2.739 0.006159 **
Tranmilescap            -3.622e-02  1.106e-02  -3.273 0.001063 **
Urban                    1.026e+00  2.169e-01   4.731 2.23e-06 ***
Hhincttl:Htppopdn        9.064e-10  3.248e-10   2.791 0.005259 **
Hhincttl:Tranmilescap    9.504e-07  2.446e-07   3.886 0.000102 ***
Hhincttl:Urban           1.973e-05  7.410e-06   2.662 0.007772 **
Htppopdn:Tranmilescap    9.627e-07  4.491e-07   2.144 0.032065 *
Htppopdn:Urban          -5.506e-05  1.529e-05  -3.602 0.000316 ***
Htppopdn:Fwylnmicap     -1.193e-04  5.153e-05  -2.315 0.020601 *
Tranmilescap:Fwylnmicap  5.770e-02  2.058e-02   2.803 0.005059 **

Two Driving Age Persons in Household
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)           -1.429e+00  1.484e-01  -9.634  < 2e-16 ***
Hhincttl              -6.791e-05  4.997e-06 -13.589  < 2e-16 ***
Hhincttl:Htppopdn      1.417e-09  1.981e-10   7.152 8.53e-13 ***
Hhincttl:OnlyElderly  -3.554e-05  7.050e-06  -5.041 4.64e-07 ***
Htppopdn:Tranmilescap  1.847e-06  1.660e-07  11.124  < 2e-16 ***

Three or More Driving Age Persons in Household
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)             -3.492e+00  4.858e-01  -7.188 6.57e-13 ***
Hhincttl                -4.904e-05  8.119e-06  -6.040 1.54e-09 ***
Htppopdn                 9.719e-05  1.763e-05   5.513 3.53e-08 ***
Hhincttl:Htppopdn        7.307e-10  3.582e-10   2.040 0.041376 *
Tranmilescap:Fwylnmicap  7.553e-02  2.283e-02   3.308 0.000938 ***
```

TABLE 19. METROPOLITAN AREA <1 VEHICLE PER DRIVING AGE PERSON HOUSEHOLD MODELS

```
Two Driving Age Persons in Household
                           Estimate Std. Error z value Pr(>|z|)    
(Intercept)              -2.626e-01  9.576e-02  -2.743 0.006095 ** 
Hhincttl                 -4.587e-05  2.306e-06 -19.893  < 2e-16 ***
Htppopdn                  5.648e-05  1.334e-05   4.235 2.28e-05 ***
OnlyElderly               1.736e+00  3.274e-01   5.302 1.15e-07 ***
Hhincttl:Htppopdn         1.192e-09  9.585e-11  12.434  < 2e-16 ***
Hhincttl:Tranmilescap     3.343e-07  5.091e-08   6.566 5.15e-11 ***
Hhincttl:OnlyElderly      9.356e-06  2.661e-06   3.516 0.000438 ***
Htppopdn:Tranmilescap    -1.428e-06  2.444e-07  -5.843 5.13e-09 ***
Htppopdn:Urban           -4.753e-05  1.013e-05  -4.694 2.68e-06 ***
Htppopdn:OnlyElderly     -2.711e-05  9.643e-06  -2.811 0.004933 ** 
Tranmilescap:Urban        2.945e-02  3.836e-03   7.677 1.63e-14 ***
OnlyElderly:Tranmilescap -1.290e-02  5.222e-03  -2.470 0.013501 *  
OnlyElderly:Fwylnmicap   -1.380e+00  3.750e-01  -3.682 0.000232 ***

Three or More Driving Age Persons in Household
                        Estimate Std. Error z value Pr(>|z|)    
(Intercept)            9.337e-01  1.027e-01   9.089  < 2e-16 ***
Hhincttl              -1.832e-05  1.521e-06 -12.042  < 2e-16 ***
OnlyElderly            5.205e+00  2.324e+00   2.240   0.0251 *  
Hhincttl:Tranmilescap  1.661e-07  3.034e-08   5.475 4.38e-08 ***
Hhincttl:Urban         1.311e-05  2.087e-06   6.283 3.32e-10 ***
Hhincttl:OnlyElderly  -1.203e-04  5.427e-05  -2.216   0.0267 *  
Urban:Htppopdn        -4.893e-05  9.915e-06  -4.935 8.01e-07 ***
Htppopdn:Fwylnmicap    8.933e-05  1.906e-05   4.686 2.79e-06 ***
Urban:Fwylnmicap      -6.891e-01  3.264e-01  -2.112   0.0347 *  
```

TABLE 20. METROPOLITAN AREA ONE-VEHICLE PER DRIVING AGE PERSON HOUSEHOL MODELS

```
One Driving Age Person in Household

                          Estimate Std. Error z value Pr(>|z|)
(Intercept)              6.222e-01  1.045e-01   5.951 2.67e-09 ***
Tranmilescap             2.328e-02  4.732e-03   4.920 8.65e-07 ***
Hhincttl:Htppopdn        1.133e-09  1.246e-10   9.090  < 2e-16 ***
Tranmilescap:Hhincttl   -2.761e-07  5.167e-08  -5.342 9.17e-08 ***
Hhincttl:OnlyElderly     7.203e-06  2.714e-06   2.654  0.00796 **
Tranmilescap:Htppopdn   -1.664e-06  2.238e-07  -7.436 1.04e-13 ***
Htppopdn:Urban          -4.537e-05  7.850e-06  -5.779 7.50e-09 ***
Htppopdn:Fwylnmicap      4.083e-05  1.643e-05   2.484  0.01298 *
Tranmilescap:OnlyElderly -7.755e-03  3.335e-03  -2.326  0.02004 *

Two Driving Age Persons in Household
                       Estimate Std. Error z value Pr(>|z|)
(Intercept)           1.531e-01  6.947e-02   2.204 0.027558 *
Hhincttl              5.789e-06  8.570e-07   6.755 1.43e-11 ***
Htppopdn              4.023e-05  1.156e-05   3.479 0.000503 ***
Urban                -3.814e-01  1.624e-01  -2.349 0.018817 *
OnlyElderly          -5.543e-01  1.212e-01  -4.575 4.77e-06 ***
Hhincttl:Htppopdn     2.409e-10  1.200e-10   2.008 0.044633 *
Hhincttl:Urban        8.177e-06  2.116e-06   3.864 0.000112 ***
Hhincttl:OnlyElderly  7.113e-06  2.141e-06   3.322 0.000894 ***
Htppopdn:Tranmilescap -1.791e-06  2.102e-07  -8.519  < 2e-16 ***
Htppopdn:Urban       -4.942e-05  8.971e-06  -5.509 3.61e-08 ***

Three or More Driving Age Persons in Household
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)        -1.279e+00  1.266e-01 -10.099  < 2e-16 ***
Hhincttl            7.911e-06  1.424e-06   5.555 2.78e-08 ***
Htppopdn           -5.763e-05  1.660e-05  -3.472 0.000517 ***
Hhincttl:Htppopdn   5.384e-10  1.809e-10   2.975 0.002928 **
Tranmilescap:Urban -2.037e-02  4.390e-03  -4.640 3.49e-06 ***
```

TABLE 21. METROPOLITAN AREA >1 VEHICLE PER DRIVING AGE PERCON HOUSEHOLD MODELS

```
One Driving Age Person in Household
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)           -1.747e+00  1.022e-01 -17.089  < 2e-16 ***
Hhincttl               1.608e-05  1.319e-06  12.195  < 2e-16 ***
Htppopdn              -5.673e-05  1.921e-05  -2.953 0.003152 **
OnlyElderly           -1.020e+00  2.698e-01  -3.782 0.000156 ***
Htppopdn:Tranmilescap -1.185e-06  4.229e-07  -2.801 0.005097 **
Htppopdn:Urban         4.531e-05  1.736e-05   2.610 0.009065 **
Urban:Fwylnmicap      -9.457e-01  2.834e-01  -3.336 0.000848 ***
OnlyElderly:Fwylnmicap 1.107e+00  4.190e-01   2.643 0.008227 **

Two Driving Age Persons in Household
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)           -1.963e+00 1.214e-01 -16.164  < 2e-16 ***
Hhincttl               7.569e-06 9.766e-07   7.750 9.19e-15 ***
Fwylnmicap             7.635e-01 1.544e-01   4.944 7.65e-07 ***
OnlyElderly           -6.649e-01 9.620e-02  -6.912 4.77e-12 ***
Hhincttl:Htppopdn      5.781e-10 1.552e-10   3.725 0.000195 ***
Htppopdn:Tranmilescap -1.265e-06 3.294e-07  -3.841 0.000123 ***
Htppopdn:Urban         2.865e-05 1.424e-05   2.012 0.044250 *
Fwylnmicap:Htppopdn   -1.559e-04 2.392e-05  -6.520 7.03e-11 ***
Tranmilescap:Urban    -2.274e-02 5.741e-03  -3.961 7.47e-05 ***

Three or More Driving Age Persons in Household
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)       -1.001e+00  1.144e-01  -8.751  < 2e-16 ***
Htppopdn          -3.012e-04  3.553e-05  -8.478  < 2e-16 ***
Tranmilescap      -1.285e-02  3.713e-03  -3.462 0.000537 ***
Htppopdn:Hhincttl  2.205e-09  3.311e-10   6.659 2.76e-11 ***
```

Figure 17 compares observed and estimated percentages of households by vehicle ownership category for each household income group. The estimated percentages match the observed values fairly well. However, for the $0 to $20,000 income group, the model underestimates the proportion of zero vehicle households and overestimates the proportion of households owning as many vehicles as driving age persons.

FIGURE 17. OBSERVED AND ESTIMATED METROPOLITAN HOUSEHOLD PROPORTIONS BY VEHICLE OWNERSHIP CATEGORY AND INCOME GROUP

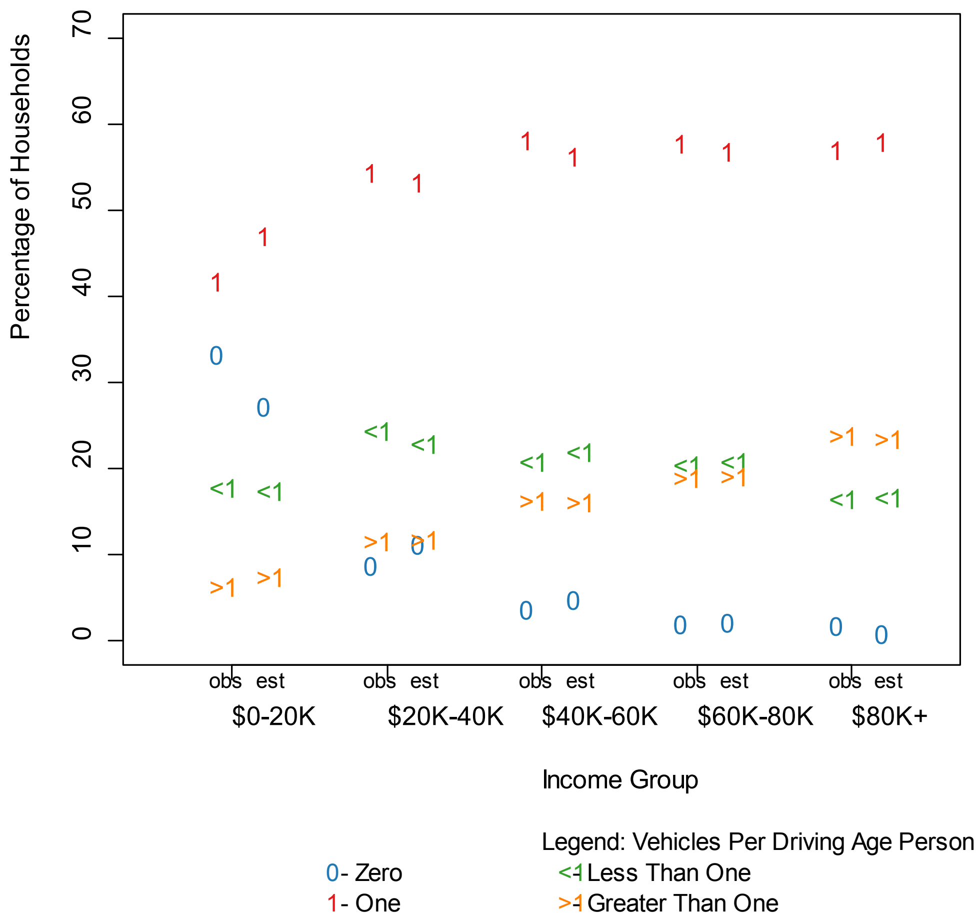
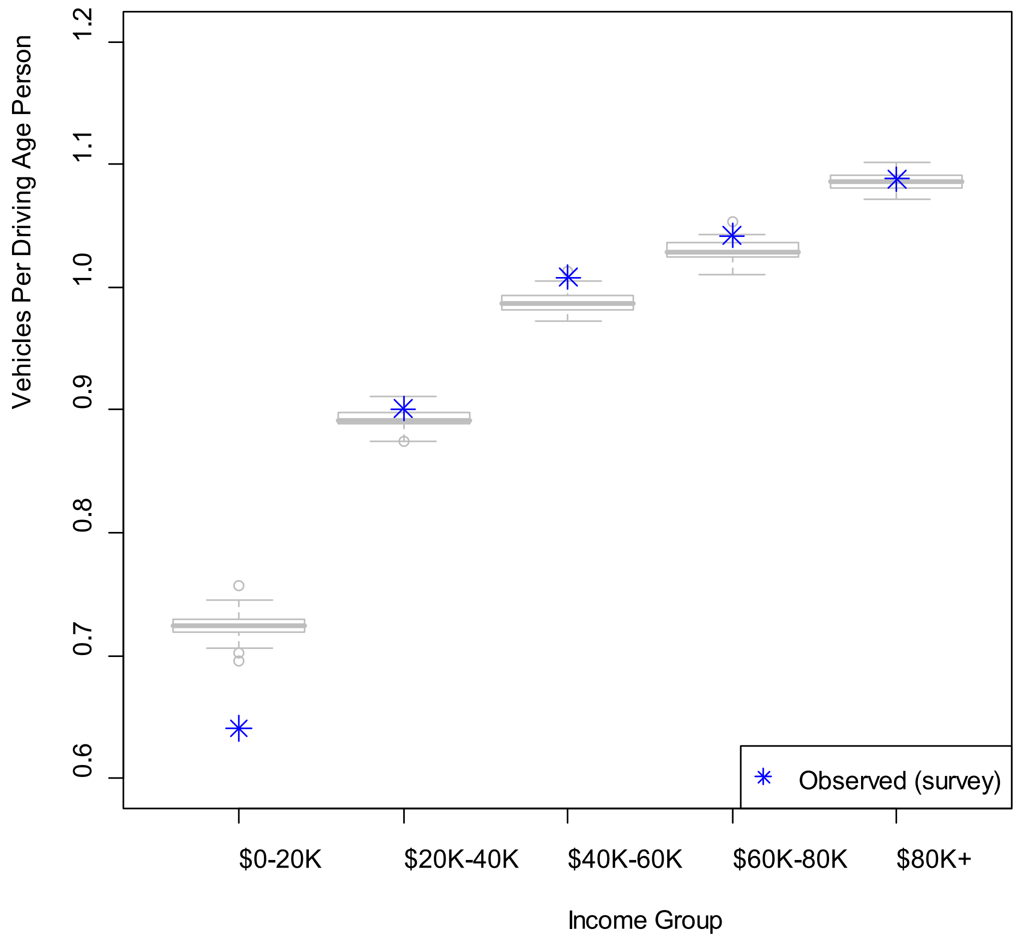


Figure 18 compares the observed and estimated average vehicle ownership ratios by income group. Except for the lowest income group, the observed means for the estimation dataset are within the range of average values produced by 50 simulations using the estimation dataset input values. The overestimation of vehicle ownership for the lower income households is consistent with the underestimation of zero-vehicle households shown in Figure 17. Since vehicle ownership affects vehicle travel, this overestimate can be expected to result in an overestimate of vehicle travel by lower income households as well. However, since these households travel less and are a small percentage of all households, the effect on total emissions will be small.

FIGURE 18. OBSERVED AND ESTIMATED MEAN VEHICLE OWNERSHIP RATIOS FOR METROPOLITAN HOUSEHOLDS BY INCOME GROUP



Tables 22, 23, 24 and 25 show the statistics for the non-metropolitan area zero vehicle, less than one vehicle, one vehicle, and greater than one vehicle models, respectively. The variables in the models have the same meanings as for the metropolitan models. The non-metropolitan models are much simpler because they do not include the variables that are unique to the metropolitan models.

TABLE 22. NON-METRO AREA ZERO-VEHICLE HOUSEHOLD MODELS

```
One Driving Age Person in Household
                       Estimate Std. Error z value Pr(>|z|)
(Intercept)          -7.647e-01  9.158e-02  -8.350  < 2e-16 ***
Hhincttl             -9.488e-05  5.071e-06 -18.712  < 2e-16 ***
Htppopdn              5.588e-05  1.263e-05   4.424 9.67e-06 ***
Hhincttl:Htppopdn     1.551e-09  4.421e-10   3.509  0.00045 ***
Htppopdn:OnlyElderly  3.445e-05  1.255e-05   2.746  0.00604 **

Two Driving Age Persons in Household
                       Estimate Std. Error z value Pr(>|z|)
(Intercept)          -1.972e+00  1.576e-01 -12.510  < 2e-16 ***
Hhincttl             -8.500e-05  5.674e-06 -14.982  < 2e-16 ***
Htppopdn              9.493e-05  1.239e-05   7.663 1.82e-14 ***
OnlyElderly          -7.510e-01  2.320e-01  -3.237  0.00121 **
Htppopdn:OnlyElderly  6.906e-05  3.020e-05   2.287  0.02222 *

Three or More Driving Age Persons in Household
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.183e+00  3.134e-01 -10.155  < 2e-16 ***
Hhincttl    -4.997e-05  8.047e-06  -6.210 5.29e-10 ***
Htppopdn     1.334e-04  2.142e-05   6.229 4.68e-10 ***
```

TABLE 23. NON-METRO AREA <1 VEHICLE PER DRIVING AGE PERSON HOUSEHOLD MODELS

```
Two Driving Age Persons in Household
                       Estimate Std. Error z value Pr(>|z|)
(Intercept)          -4.139e-01  6.274e-02  -6.596 4.22e-11 ***
Hhincttl             -3.932e-05  1.432e-06 -27.452  < 2e-16 ***
Htppopdn              4.706e-05  1.035e-05   4.548 5.43e-06 ***
OnlyElderly           3.036e-01  9.549e-02   3.179  0.00148 **
Hhincttl:Htppopdn     9.677e-10  2.003e-10   4.832 1.35e-06 ***
Hhincttl:OnlyElderly  1.539e-05  2.323e-06   6.624 3.51e-11 ***

Three or More Driving Age Persons in Household
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  4.815e-01  5.982e-02   8.049 8.36e-16 ***
Hhincttl    -1.262e-05  8.471e-07 -14.898  < 2e-16 ***
Htppopdn     9.046e-05  9.435e-06   9.588  < 2e-16 ***
OnlyElderly  1.832e+00  4.891e-01   3.745 0.000181 ***
```

Table 24. Non-Metro Area One-Vehicle Per Driving Age Person Household Models

```
One Driving Age Person in Household
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)          9.734e-01  6.127e-02  15.887  < 2e-16 ***
Hhincttl            -9.718e-06  1.436e-06  -6.768 1.30e-11 ***
Htppopdn            -2.844e-05  1.111e-05  -2.559  0.01050 *
OnlyElderly          2.546e-01  9.350e-02   2.723  0.00647 **
Hhincttl:Htppopdn    1.494e-09  2.916e-10   5.123 3.01e-07 ***
Hhincttl:OnlyElderly 6.460e-06  2.565e-06   2.519  0.01177 *
Htppopdn:OnlyElderly -2.758e-05  1.304e-05  -2.115  0.03443 *

Two Driving Age Persons in Household
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)          2.441e-01  4.015e-02   6.082 1.19e-09 ***
Hhincttl             2.214e-06  6.312e-07   3.508 0.000451 ***
Htppopdn            -5.871e-05  1.009e-05  -5.821 5.85e-09 ***
OnlyElderly         -3.624e-01  7.922e-02  -4.575 4.76e-06 ***
Hhincttl:Htppopdn    1.287e-09  1.792e-10   7.184 6.77e-13 ***
Hhincttl:OnlyElderly 7.835e-06  1.573e-06   4.980 6.36e-07 ***
Htppopdn:OnlyElderly -5.577e-05  1.447e-05  -3.854 0.000116 ***

Three or More Driving Age Persons in Household
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.088e+00  6.337e-02 -17.167  < 2e-16 ***
Hhincttl     7.315e-06  8.474e-07   8.632  < 2e-16 ***
Htppopdn    -5.232e-05  1.001e-05  -5.225 1.74e-07 ***
```

Table 25. Non-Metro Area >1 Vehicle Per Driving Age Person Household Models

```
One Driving Age Person in Household
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)         -1.510e+00  5.865e-02 -25.739  < 2e-16 ***
Hhincttl             1.978e-05  1.173e-06  16.867  < 2e-16 ***
Htppopdn            -1.011e-04  1.106e-05  -9.137  < 2e-16 ***
OnlyElderly         -5.025e-01  8.011e-02  -6.273 3.54e-10 ***
Htppopdn:OnlyElderly -8.931e-05  2.958e-05  -3.019  0.00254 **

Two Driving Age Persons in Household
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)         -1.292e+00  4.012e-02 -32.201   <2e-16 ***
Hhincttl             9.130e-06  5.564e-07  16.409   <2e-16 ***
Htppopdn            -1.275e-04  8.576e-06 -14.862   <2e-16 ***
OnlyElderly         -5.888e-01  6.582e-02  -8.946   <2e-16 ***
Htppopdn:OnlyElderly -6.491e-05  3.090e-05  -2.101   0.0357 *

Three or More Driving Age Persons in Household
(Intercept) -1.894e+00  7.757e-02 -24.413  < 2e-16 ***
Hhincttl     1.033e-05  9.970e-07  10.364  < 2e-16 ***
Htppopdn    -1.280e-04  1.583e-05  -8.089 6.01e-16 ***
```

Figure 19 compares observed and estimated percentages of households by vehicle ownership category for each household income group. The estimated percentages match the observed values fairly well. The differences in the observed and estimated proportions for the $0 to

$20,000 income group are not as great as was the case with the metropolitan household comparison. However, greater differences can be seen in the less than one and greater than one vehicle per driving age person households in the $40,000 - $60,000 income group and the $60,000 - $80,000 income group.

FIGURE 19. OBSERVED AND ESTIMATED NON-METROPOLITAN HOUSEHOLD PROPORTIONS BY VEHICLE OWNERSHIP CATEGORY AND INCOME GROUP

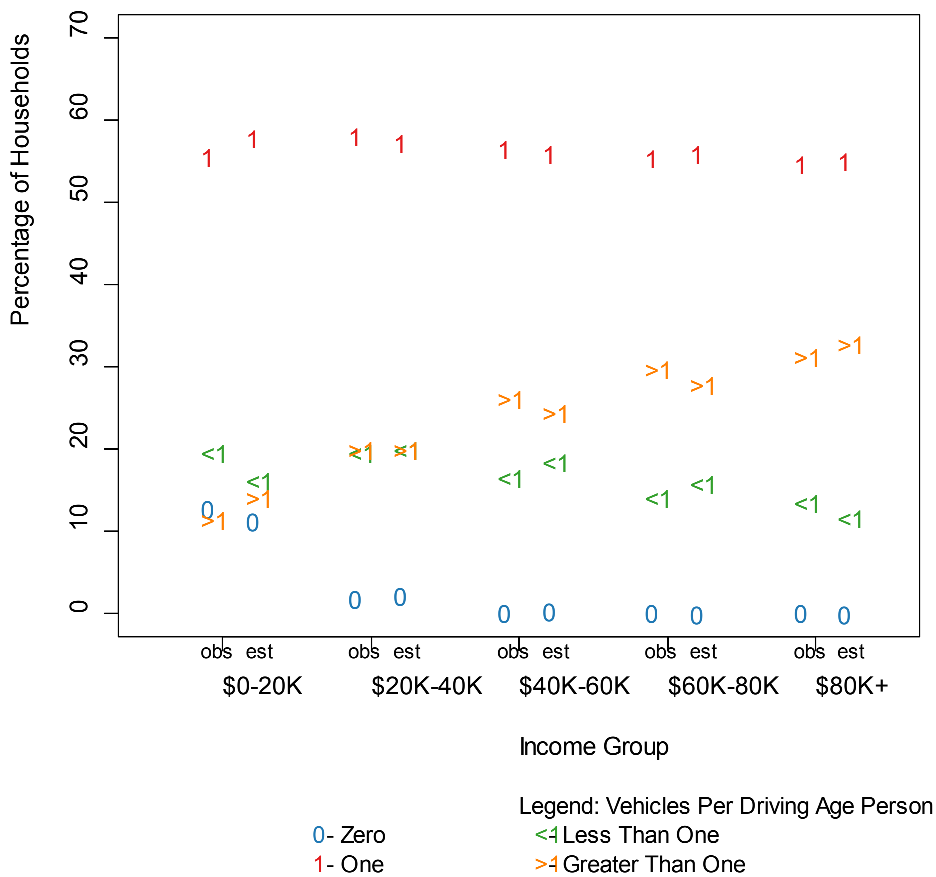
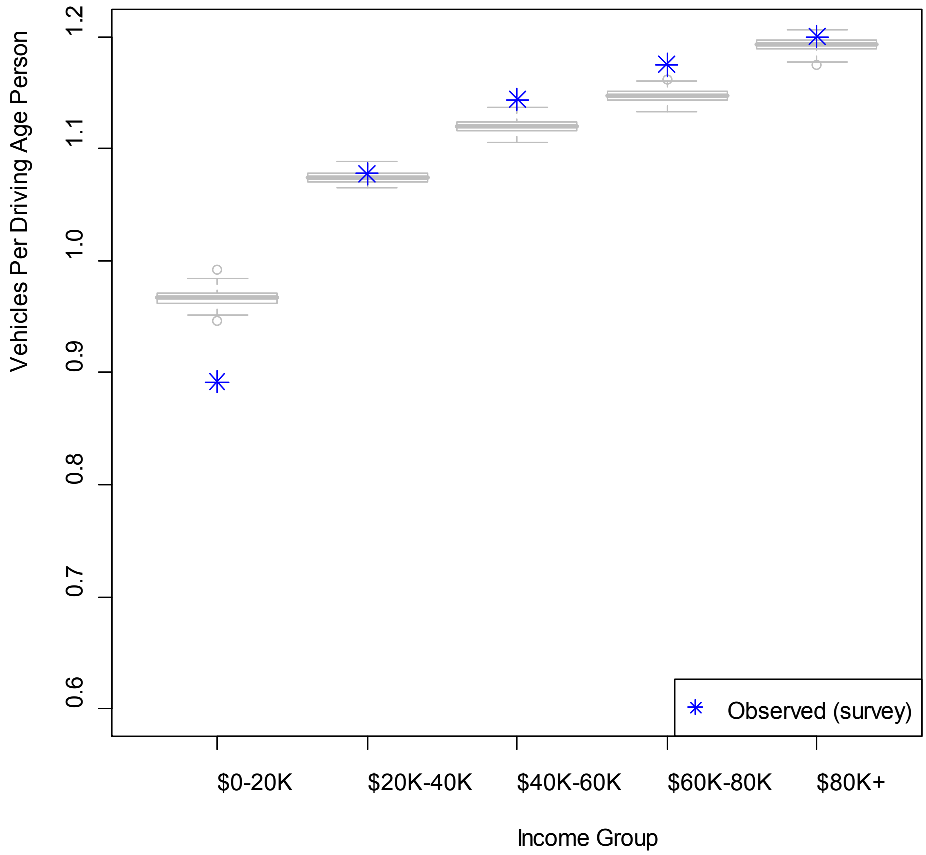


Figure 20 compares the observed and estimated average vehicle ownership ratios by income group. As with the metropolitan household data, the model overestimates vehicle ownership for the lowest income group. The model also underestimates vehicle ownership in the $40,000 - $60,000 and $60,000 - $80,000 income groups. This latter difference, however, is quite small. The overestimation of lower income household vehicle ownership will have a very small effect on emissions calculations because these households are a small percentage of the total and they travel less than households in higher income groups.

FIGURE 20. OBSERVED AND ESTIMATED MEAN VEHICLE OWNERSHIP RATIOS FOR NON-METROPOLITAN HOUSEHOLDS BY INCOME GROUP



The number of vehicles assigned to each household is computed by vehicle ownership category. Obviously, the number is zero for the first ownership category and is equal to the number of driving age persons for the third ownership category. For the other two categories, tabulations of numbers of households by number of vehicles owned were made from the estimation dataset. These tabulations were converted into proportions that are used as probabilities in a Monte Carlo process to assign the number of vehicles to the household.

Car-Sharing

The effects of car-sharing on vehicle travel are addressed through vehicle ownership and the variable costs of vehicle travel paid by participants, relative to the fuel costs paid by vehicle owners. Since car-sharing is a relatively new phenomenon, it is not addressed in NHTS data and there are no definitive data to use in a model. The approach, therefore, is approximate and relies primarily on research by Cambridge Systematics[5] and Martin and Shaheen[6], and research documented by Millard-Ball[7] and the Victoria Transportation Policy Institute[8].

[5] Cambridge Systematics, "Moving Cooler: An Analysis of Transportation Strategies for Reducing Greenhouse Gas Emissions", Urban Land Institute, Washington, D.C., October 2009, pp. B-51 to B-52.

The scope of car-sharing programs is specified as a model input using the approach documented for the *Moving Cooler* study. The number of car-share vehicles per 2,000 inhabitants of medium density Census tracts (4,000 – 10,000 persons per square mile) and the number per 1,000 inhabitants of high density Census tracts (> 10,000 persons per square mile) are specified for each metropolitan area. The target number of households that participate in car-sharing is calculated based on the assumption that there are 20 participating households per car-share vehicle, on average.

Individual households in the two density categories are identified as candidate participants based on their household characteristics. According Martin and Shaheen's, analysis of a survey of almost 10,000 carsharing persons in North America, carsharing households have the following characteristics:

- Low car ownership prior to joining: About 60% owned no cars. About 30% owned one car. Almost all of the rest owned two cars.
- Small households: The average is 1.9 persons compared to a U.S. average of 2.6 persons.
- Younger adults: The average age is about 37 years. About 10% are 55 or older. About 2% are 65 or older.
- Incomes are distributed across the spectrum, but the average income is higher than the population average.
- Above average education: Over 80% have a bachelor's degree or advanced degree.

Given the lack of comprehensive disaggregate data on car sharing, the model for identifying carsharing households is synthesized. The basic approach is to develop weights for each key carsharing attribute. Only three of the attributes listed above (car ownership, household size, and age of household persons) are used. Household Income is not used because the variable is continuous and no clear distinctions can be made for households participating in carsharing. Educational attainment is not used because it is not modeled in the GreenSTEP and RSPM models. Also, it is likely that the educational attainment characteristics of carshare households will change as carsharing become more a prevalent and familiar service. Age is used in a simplified manner because like income it is continuous, but unlike income there is a fairly clear distinction between older (retirement age) persons and others. The total weight assigned to each household is the product of the individual attribute weights. These weights are then used

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[6] Martin, Elliot, Susan Shaheen "Greenhouse Gas Emissions Impacts of Carsharing in North America", Mineta Transportation Institute, College of Business, San Jose State University, June 2010.

[7] Millard-Ball, Adam, et.al., "Car-Sharing: Where and How It Succeeds. TCRP Report 108, Transit Cooperative Research Program, Transportation Research Board, Washington, D.C., 2005.

[8] Victoria Transportation Policy Institute, "TDM Encyclopedia", Carsharing, https://www.vtpi.org/tdm/tdm7.htm

in a Monte Carlo sampling process to choose households. Individual weights were determined in consideration of reported attributes of carsharing households and iteratively adjusting weights so that at low carsharing rates the vehicle and household size attributes of modeled carsharing households are similar to the reported attributes. Table 26 shows the attribute weights used in the model. Values of attributes not shown in the table (e.g. households owning 4 vehicles) are assigned a weight of zero.[9]

TABLE 26. ATTRIBUTE WEIGHTS USED IN THE MODEL FOR IDENTIFYING CARSHARING HOUSEHOLDS

Number of Household Vehicles Prior to Joining				
0 Vehicles	1 Vehicle	2 Vehicles	3 Vehicles	
0.8	0.15	0.048	0.002	
Household Size				
1 Person	2 Persons	3 Persons	4 Persons	>=5 Persons
0.4	0.25	0.25	0.08	0.02
Age of Persons in Household				
All Under 65	Any Over 65			
0.95	0.05			

The number of vehicles owned by carsharing households is adjusted to reflect reductions in ownership documented by Martin and Shaheen with some simplifications. Table 27 shows the probabilities used in the model to adjust vehicles ownership based on the number of vehicles owned prior to joining. Although Martin and Shaheen report some small increases in vehicle ownership after households joined carsharing groups[10], it is assumed that this was due to factors other than carsharing. The probabilities shown in Table 27 are applied stochastically to adjust the number of cars owned by carsharing households. After this reduction, the household vehicle ownership of all car-sharing households is increased by 1/20th of a vehicle to account for the availability of a car-share vehicle.

[9] A previous version of the model used a rule-based approach to identifying carsharing households. Rules identifying candidate households were successively relaxed as needed to identify a sufficient number of households. This approach was abandoned because it introduced very apparent discontinuities in the results as the numbers of carsharing households were increased.

[10] About 5% of zero-vehicle households, 1% of one-vehicle households, and 1% of two-vehicle households increased their vehicle ownership after joining carsharing organizations.

TABLE 27. CAR OWNERSHIP PROBABILITY FOR CARSHARING HOUSEHOLDS BY NUMBER OF VEHICLES OWNED PRIOR TO JOINING

Number of Cars Prior to Joining	Probability of Number of Cars After Joining			
	0 Cars	1 Car	2 Cars	3 Cars
0 Cars	1	0	0	0
1 Car	0.66	0.34	0	0
2 Cars	0.17	0.56	0.27	0
3 Cars	0.15	0.21	0.22	0.42

The average household cost per mile for carshare households is adjusted to reflect that car-share users pay the full cost of using a car-share vehicle per mile of travel. Based on the values reported the TDM Encyclopedia, the variable (per mile) cost of using a carshare vehicle is about 5 times more than the variable cost of using a privately owned vehicle.

The revised mileage cost for the carshare household is calculated as:

(AGCMVO * VO + 5 * AGCM * 0.05) / (VO + 0.05)

where:

AGCMVO = average gas cost per mile for the vehicles owned by the household

VO = number of vehicles owned by the household

AGCM = average gas cost per mile for the population

The mileage cost for zero-car households who are not carsharing participants is calculated at 7.5 times the average gas cost per mile of households in the area.

Tables 28 and 29 show the results of testing the model on the survey households at different participation levels. Table 28 shows the percentage of carshare households by number of vehicles owned before and after adjusting vehicle ownership at different participation rates. At the lowest rate of carshare participation, shown in the first row, the split of households among vehicle ownership groups is similar to the before and after distributions reported by Martin and Shaheen: before = 62% 0-veh., 31% 1-veh., 7% 2-veh.; after = 80% 0-veh., 17% 1-veh., 3% 2-veh..

Table 29 shows how average vehicle ownership and DVMT changes for carshare households before and after vehicle adjustment. The average vehicle ownership rate at the lowest levels of carshare participation is similar to that reported by Martin, Shaheen and Lidicker (Before = 0.47, After = 0.24).[11] Martin et.al. did not estimate the effect of carshare participation on household DVMT but this was done by Cervero, Golub and Nee with carshare survey data for the San

[11] Martin, Elliot, Susan Shaheen, Jeffrey Lidicker, *Carsharing's Impact on Household Vehicle Holdings: Results from a North American Shared-use Vehicle Survey*, Transportation Research Board Annual Meeting 2010, Paper #10-3437, Transportation Research Board, Washington, DC.

Francisco Bay area.[12] Using survey data for carshare households and a set of similar households that were interested in joining carsharing, they estimated a model of average household DVMT as a function of household and other characteristics. Their model predicted that on average, participation in carsharing reduced household DVMT by 7.08 miles. The average reduction predicted by the GreenSTEP and RSPM models for the lowest participation level is 7.1 miles.

TABLE 28. BEFORE AND AFTER SPLIT OF CARSHARE HOUSEHOLDS AMONG VEHICLE OWNERSHIP LEVELS BY PARTICIPATION RATES

Participation Rates (Pop / Vehicles)	Before Vehicle Adjustment				After Vehicle Adjustment			
	0 Veh	1 Veh	2 Veh	3 Veh	0 Veh	1 Veh	2 Veh	3 Veh
High Den. = 1000 Med. Den. = 2000	58.2%	33.0%	8.9%	0%	82.2%	15.6%	2.2%	0%
High Den. = 500 Med. Den. = 1000	56.4%	34.8%	8.9%	0%	80.7%	16.8%	2.5%	0%
High Den. = 250 Med. Den. = 500	51.5%	38.2%	10.4%	0%	78.5%	18.7%	2.8%	0%
High Den. = 125 Med. Den. = 250	40.9%	46.1%	12.7%	0.3%	73.6%	22.8%	3.5%	0.1%
High Den. = 60 Med. Den. = 125	28.9%	48.3%	22.3%	0.5%	64.6%	29.1%	6.1%	0.2%

[12] Cervero, Robert, Aaron Golub, and Brendan Nee. City CarShare, Longer-Term Travel Demand and Car Ownership Impacts, Transportation Research Record: Journal of the Transportation Research Board, No. 1992, Washington D.C. 2007, pp. 70-80

TABLE 29. BEFORE AND AFTER AVERAGE HOUSEHOLD DVMT OF CARSHARE HOUSEHOLDS BY PARTICIPATION RATES

Participation Rates (Pop / Vehicles)	Mean Household Size	Before Vehicle Adjustment		After Vehicle Adjustment	
		Ownership Rate	DVMT	Ownership Rate	DVMT
High Den. = 1000 Med. Den. = 2000	1.79	0.47	14.8	0.19	7.7
High Den. = 500 Med. Den. = 1000	1.82	0.49	15.5	0.20	8.3
High Den. = 250 Med. Den. = 500	1.77	0.58	17.6	0.23	9.3
High Den. = 125 Med. Den. = 250	1.87	0.71	21.2	0.29	11.2
High Den. = 60 Med. Den. = 125	1.97	0.94	26.2	0.42	15.0
High Den. = 30 Med. Den. = 60	2.2	1.24	33.0	0.61	21.0

The model results show that the before adjustment vehicle ownership rates and average household DVMT increase as the rate carsharing participation increases. This is consistent with the inclusion of larger households and households owning more vehicles in the carsharing pool. This will happen if carsharing grows beyond the niche it presently occupies.

Calculate Initial Household DVMT

The household vehicle travel model component is the most important component of the GreenSTEP and RSPM models. The main purpose of this component is to calculate the average daily vehicle miles traveled (DVMT). The calculation is sensitive to household characteristics, land use and transportation system characteristics, and vehicle travel costs. Separate models are estimated for metropolitan and non-metropolitan areas. The average household DVMT is used in the calculation of the amount of energy consumed and the greenhouse gas emissions that result from the fuel consumption. The model also calculates the 95th percentile DVMT and the maximum DVMT for the household. These values are used in the electric vehicle model to determine whether a household vehicle is a candidate for an electric vehicle.

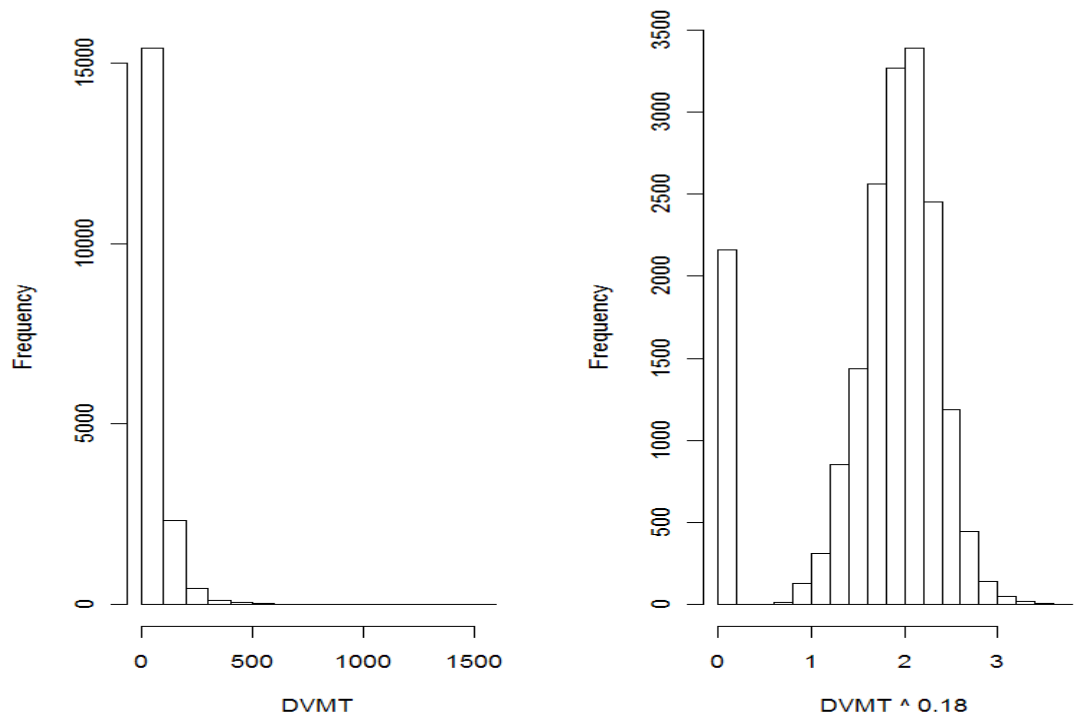
This model component is also the most complex to estimate because data on the average household DVMT is not included in the survey and must be imputed. This is done using simulation. Metropolitan and non-metropolitan models are estimated to determine the probability that a household engages in no vehicle travel on any given day. Models are also estimated to calculate the amount of vehicle travel a household is likely to do if it engages in vehicle travel for the day. In addition, a stochastic error term is applied to this model to reflect day-to-day variability in household travel. The rationale for this is explained in more detail below. A likely distribution of DVMT is calculated for each household by running these two models hundreds of times. The household DVMT distribution is used to calculate the household's average DVMT, 95th percentile DVMT and maximum DVMT.

Although this simulation approach is a very useful for calculating average household DVMT, it is also very time and memory intensive and becomes a significant liability if used in the final model. But once these values were calculated for the survey households, a linear model was estimated to predict average household DVMT as a function of the same variables used to calculate the stochastic models. Linear models were also estimated to calculate a household's 95th percentile DVMT and maximum DVMT as a function of the household's average DVMT.

The first step in developing the household travel model was to develop stochastic models to model a distribution of likely household DVMT on any given day. The stochastic household travel model has two components. The first component determines the likelihood that a household engaged in no vehicle travel for the day and this component is implemented with a binomial logit model. The second component is a linear model that predicts the vehicle miles traveled for households that did some vehicle travel.

As with income, household vehicle travel follows a power distribution. This is shown in the histogram on the left side of Figure 21. Because the distribution is not normal, transformation is in order to improve the model fit and produce more uniform distribution of residuals. A power transformation with an exponent of 0.18 for metropolitan households and 0.15 for non-metropolitan households minimizes the skewness of the distribution. This is shown in the right-hand plot.

FIGURE 21. METROPOLITAN HOUSEHOLD DVMT AND POWER TRANSFORMED DVMT



The right-hand plot illustrates why it is necessary to use two models to predict household DVMT. The power transform of household DVMT places the zero DVMT households in a grouping that is discontinuous with the households that have some vehicle travel. Including the zero DVMT households with the other households would distort the model.

The zero DVMT household model is a binary logit model which predicts the probability that a household does no vehicle travel. As with other household models in the GreenSTEP and RSPM models, there are separate models for metropolitan and non-metropolitan area households because additional land use and transportation factors in metropolitan areas affect household vehicle travel decisions.

Table 30 shows the metropolitan model coefficients and statistics. Table 31 shows this information for the nonmetropolitan models. The variable names in the tables have the following meanings:

- DrvAgePop – Number of driving age persons
- LogIncome – Natural log of annual household income
- Htppopdn – Census tract population density in persons per square mile
- Age65Plus – Number of persons 65 years old or older in the household
- Transmilescap – Annual metropolitan transit revenue miles per capita
- Hhvehcnt – Number of household vehicles
- ZeroVeh – Dummy variable indicating whether the household owns no vehicles

- Tranmilescap:Urban – Interaction of transit revenue miles per capita with a dummy variable indicating whether household is in an urban mixed-use area
- Age30to54 – Number of persons in the 30 to 54 age bracket

TABLE 30. METROPOLITAN AREA ZERO DVMT HOUSEHOLD MODELS

```
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)          3.700e+00  3.437e-01  10.767  < 2e-16 ***
DrvAgePop           -5.223e-01  4.489e-02 -11.635  < 2e-16 ***
LogIncome           -4.860e-01  3.466e-02 -14.023  < 2e-16 ***
Htppopdn             2.983e-05  4.541e-06   6.569 5.08e-11 ***
Age65Plus            3.196e-01  3.883e-02   8.232  < 2e-16 ***
Tranmilescap         8.369e-03  2.182e-03   3.836 0.000125 ***
Hhvehcnt            -3.611e-01  4.762e-02  -7.582 3.39e-14 ***
ZeroVeh              3.427e+00  1.228e-01  27.905  < 2e-16 ***
Tranmilescap:Urban   1.086e-02  2.371e-03   4.578 4.68e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 17611  on 19526  degrees of freedom
Residual deviance: 10042  on 19518  degrees of freedom
AIC: 10060

Number of Fisher Scoring iterations: 6
```

TABLE 31. NON-METROPOLITAN AREA ZERO DVMT HOUSEHOLD MODELS

```
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)          4.861e+00  2.563e-01  18.967  < 2e-16 ***
DrvAgePop           -6.299e-01  4.126e-02 -15.266  < 2e-16 ***
LogIncome           -5.772e-01  2.662e-02 -21.685  < 2e-16 ***
Htppopdn             2.109e-05  4.946e-06   4.264 2.00e-05 ***
Hhvehcnt            -1.752e-01  2.912e-02  -6.017 1.78e-09 ***
ZeroVeh              3.435e+00  1.075e-01  31.938  < 2e-16 ***
Age30to54           -1.080e-01  3.729e-02  -2.895  0.00379 **
Age65Plus            3.770e-01  3.384e-02  11.142  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 25163  on 35368  degrees of freedom
Residual deviance: 18025  on 35361  degrees of freedom
AIC: 18041

Number of Fisher Scoring iterations: 6
```

The signs of the model coefficients are as expected. The probability of zero DVMT increases with higher population density, zero vehicle ownership, higher levels of transit service, presence of urban mixed-use character, and presence of persons aged 65 or older. The probability of zero DVMT decreases with more driving age persons, higher income, more household vehicles, and more persons in the 30 to 54 age group.

The metropolitan and non-metropolitan household DVMT models are linear models, where the predicted variable is a power transform of DVMT. Power transformation of the variable normalizes the distribution, improving model fit and producing more uniform errors over the distribution. Exponents of 0.18 and 0.15 were found to minimize the skewness of the distributions for metropolitan and non-metropolitan households, respectively.

Table 32 shows the variable coefficients and statistics for the metropolitan household model. Variable names not previously described have the following meanings:

- Fwylnmicap – Metropolitan area ratio of freeway lane-miles per 1000 persons
- Htppopdn:Tranmilescap – The interaction between census tract population density and transit revenue miles per capita

TABLE 32. METROPOLITAN AREA HOUSEHOLD DVMT MODEL

```
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            7.806e-01  4.637e-02  16.836  < 2e-16 ***
Age65Plus             -7.184e-02  4.218e-03 -17.033  < 2e-16 ***
LogIncome              8.690e-02  4.239e-03  20.498  < 2e-16 ***
Htppopdn              -3.693e-06  1.141e-06  -3.236  0.00121 **
Fwylnmicap             3.381e-02  1.605e-02   2.107  0.03511 *
Urban                 -5.177e-02  8.644e-03  -5.989 2.16e-09 ***
Hhvehcnt               6.087e-02  3.234e-03  18.821  < 2e-16 ***
DrvAgePop              7.232e-02  3.680e-03  19.652  < 2e-16 ***
Htppopdn:Tranmilescap -5.980e-08  2.647e-08  -2.259  0.02391 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3378 on 16256 degrees of freedom
Multiple R-squared: 0.2119,      Adjusted R-squared: 0.2114
F-statistic: 397.4 on 11 and 16256 DF,  p-value: < 2.2e-16
```

The signs of the coefficients are as expected. Higher incomes, more vehicles, more driving age persons, and greater freeway supplies are associated with more vehicle travel. Persons age 65 or older, higher population densities, urban mixed-use characteristics, and higher levels of public transit service are associated with less vehicle travel.

Table 33 shows the variable coefficients and statistics for the non-metropolitan household model. Variable names have the same meanings as previously described.

The non-metropolitan model includes more age variables and fewer land use and transportation variables than the metropolitan model. The signs on the coefficients are as expected. Higher incomes, more household vehicles, and more people of any age increase household DVMT. Higher population density and zero-vehicle households are associated with lower household DVMT.

TABLE 33. NON-METROPOLITAN AREA HOUSEHOLD DVMT MODEL

```
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          9.231e-01  2.466e-02  37.439  < 2e-16 ***
Census_rMidwest     -1.239e-02  4.053e-03  -3.057 0.002239 **
Census_rSouth        3.033e-02  4.770e-03   6.359 2.06e-10 ***
Census_rWest        -2.650e-02  5.600e-03  -4.731 2.25e-06 ***
LogIncome            5.801e-02  2.406e-03  24.111  < 2e-16 ***
Hhvehcnt             3.422e-02  1.619e-03  21.134  < 2e-16 ***
ZeroVeh             -4.918e-02  2.321e-02  -2.118 0.034149 *
Htppopdn            -5.498e-06  1.210e-06  -4.544 5.53e-06 ***
Age0to14             8.716e-03  1.820e-03   4.790 1.68e-06 ***
Age15to19            3.667e-02  3.359e-03  10.918  < 2e-16 ***
Age20to29            9.387e-02  4.044e-03  23.215  < 2e-16 ***
Age30to54            8.366e-02  3.718e-03  22.499  < 2e-16 ***
Age55to64            7.598e-02  4.136e-03  18.370  < 2e-16 ***
Age65Plus            3.230e-02  3.919e-03   8.242  < 2e-16 ***
Htppopdn:Age20to29 -1.820e-06  8.328e-07  -2.185 0.028904 *
Htppopdn:Age30to54 -3.362e-06  7.079e-07  -4.749 2.05e-06 ***
Htppopdn:Age55to64 -3.421e-06  9.545e-07  -3.584 0.000338 ***
Htppopdn:Age65Plus -2.763e-06  8.827e-07  -3.130 0.001747 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2641 on 31303 degrees of freedom
Multiple R-squared: 0.1835,      Adjusted R-squared: 0.1831
F-statistic: 413.8 on 17 and 31303 DF,  p-value: < 2.2e-16
```

As is the case with the income model, the household travel models do not reproduce the tails of the frequency distribution. This is illustrated in Figure 22, where the distribution of the predicted power-transformed metropolitan household DVMT (red line) is compared with the survey distribution (black line). The means and medians of the estimated and observed values are very close, but since the values are power transformations, the means of untransformed DVMT do not match. The inability of the model to match the tails of the distribution results in the mean household DVMT being underestimated (Figure 23).

Adding a normally distributed random error to the model reproduces the tails of the distribution. The size of this "error term" (standard deviation) was estimated by taking the square root of the difference in the observed and estimated variances of the power-transformed DVMT. The final value was calibrated by adjusting the estimated value so that the observed and estimated DVMT means match. Figure 24 shows the estimated and calibrated standard deviation values (error term) for the power-transformed DVMT.

The effect on the power-transformed DVMT distribution is shown in Figure 22 (blue line). Figure 23 shows that when untransformed, the model distribution with the added error term matches the survey distribution very well, and the mean values are nearly the same.

FIGURE 22. OBSERVED AND ESTIMATED DISTRIBUTIONS OF POWER-TRANSFORMED DVMT FOR METROPOLITAN HOUSEHOLDS

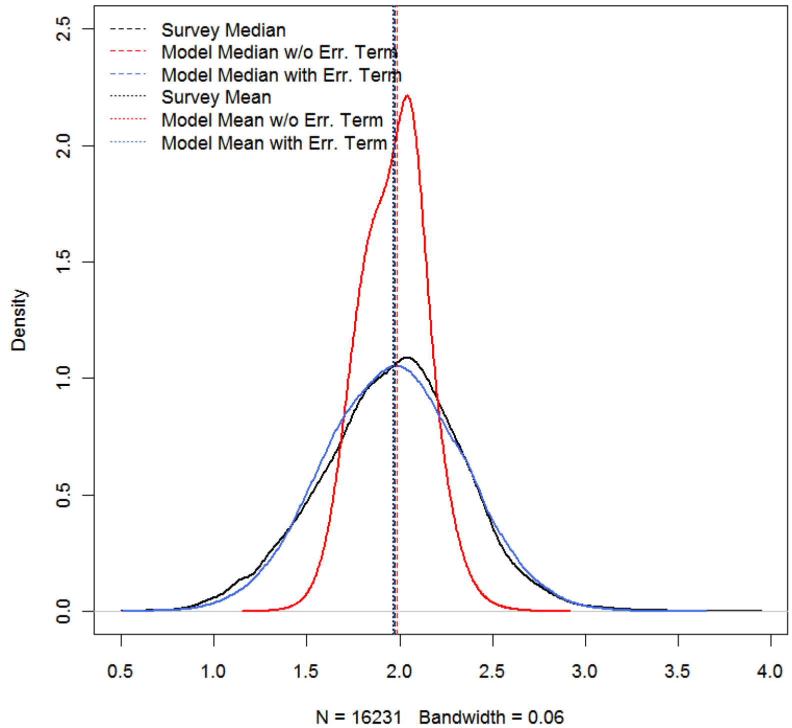


FIGURE 23. OBSERVED AND ESTIMATED DISTRIBUTIONS OF DVMT FOR METROPOLITAN HOUSEHOLDS

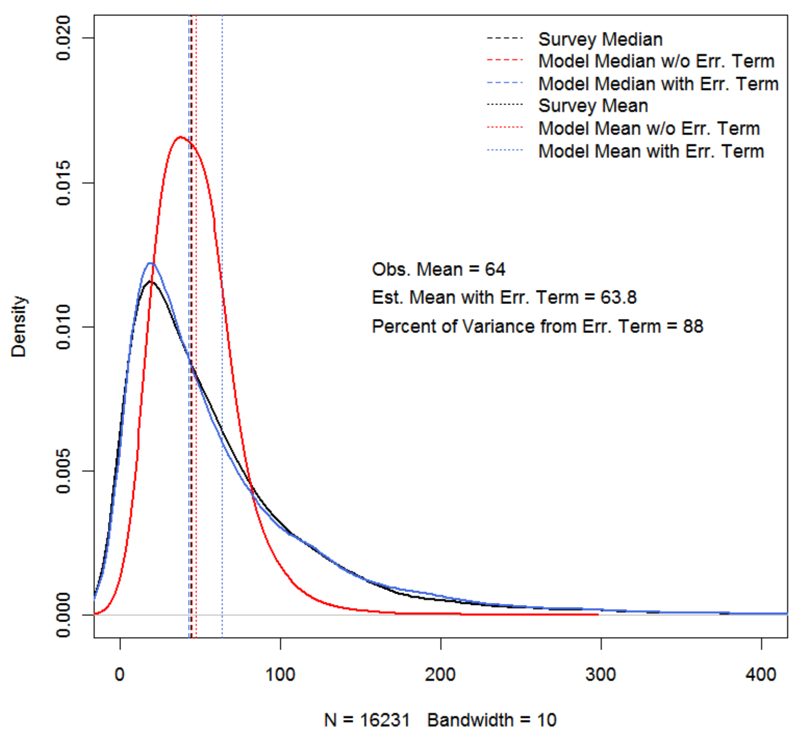
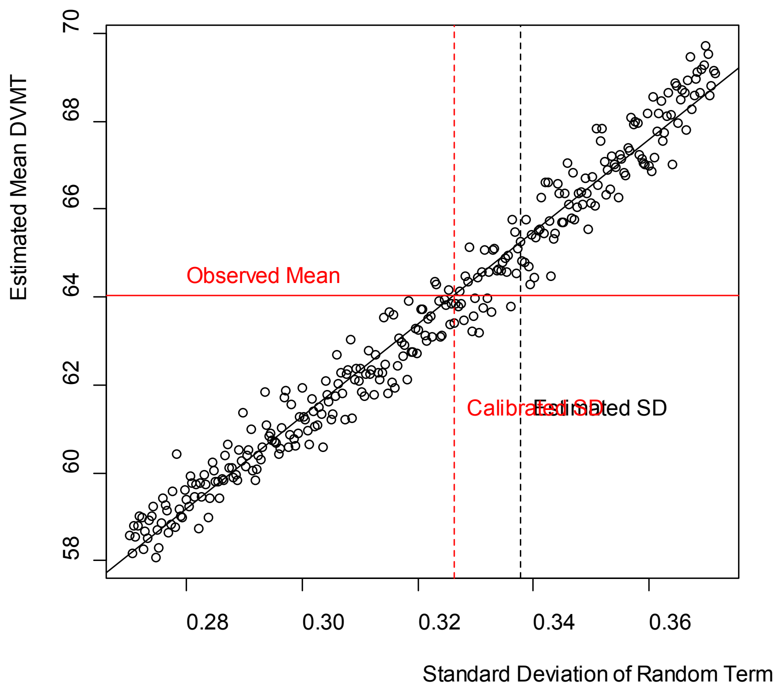


FIGURE 24. MEAN ESTIMATED HOUSEHOLD DVMT VS. STANDARD DEVIATION FOR RANDOM TERM

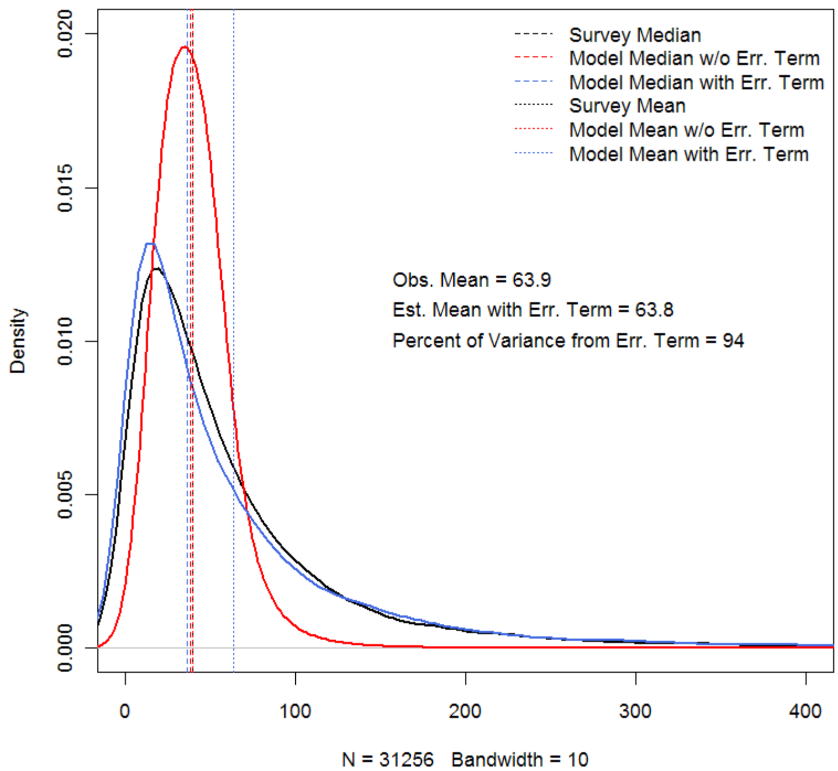


The same process was used to match the non-metropolitan model distribution to the survey distribution. Figure 25 shows the observed and estimated DVMT distributions for non-metropolitan households.

Using error terms in the metropolitan and non-metropolitan household DVMT models also provides a means of addressing the issue of how to predict an average DVMT for an individual household as well as the day-to-day distribution of DVMT for that household. Calculating an annual average is important in order to calculate annual household fuel consumption, costs, and emissions. Calculating a distribution of household DVMT is important in order to gauge how well an EV would meet a household's travel needs. It is not sufficient that an EV meet a household's average daily travel needs. To be a viable option, it must meet the large majority of the day-to-day travel needs of the household.

The challenge is that the household DVMT data used for model estimation is not the average DVMT. It is the household DVMT on the survey day. The NHTS survey, like most household travel surveys, only collects data for one survey day so it does not report household averages. This is not an issue for most travel model uses, which are concerned with predicting the numbers of travelers on different parts of the transportation system. Low predictions of daily travel for some households are balanced by high predictions of daily travel by others. This is an issue for calculating household averages and for estimating the day-to-day variation in household vehicle travel.

FIGURE 25. OBSERVED AND ESTIMATED DISTRIBUTIONS OF DVMT FOR NON-METROPOLITAN HOUSEHOLDS



Kuhnimhof and Gringmuth, using data from the multiday German Mobility Panel, found that the day-to-day variation in personal travel was much greater than the variation between persons.[13] They estimated that 70 per cent of all variance in mileage per person per day was intrapersonal (i.e. day-to-day variation in a person's travel). If this percentage holds true for variation in household DVMT, then day-to-day variation in household vehicle travel would account for 80 percent (0.7 / 0.88) of the unexplained variation in metropolitan household travel that is captured by the calibrated random error term. In the case of non-metropolitan households, it would account for 74 percent (0.7 / 0.94) of the unexplained variation.

Given the likelihood that day-to-day travel variation is mostly responsible for the unexplained variation in household travel, stochastic travel models were run thousands of times in order to develop likely distributions of vehicle travel for each household. This was done by running the zero DVMT and daily household DVMT models in tandem 100 times for each household in the survey dataset. From each set of 100 runs, the household average, 95th percentile and maximum values were calculated. This process was repeated 30 times and the results were averaged for each household. So in total, 3000 runs of the model were done for each survey household to produce the average, 95th percentile, and maximum values for the household.

[13] Kuhnimhof, Tobias and Christoph Gringmuth, pp. 178-185.

Once the average household DVMT values were imputed using simulation, linear models for calculating average DVMT models were estimated. This was done to speed up model execution, to reduce the amount of stochastic variation occurring in model results, and to simplify the estimation of a household travel budget model (described in the next section).

The simulated values of average household DVMT, like the values of household DVMT follow a power distribution. The metropolitan and non-metropolitan power transforms used for the household DVMT models were also used to transform the average household DVMT values to normalize the data to use in the linear model estimation.

The variables used in the models are the same as the variables used in the daily VMT models. Table 34 shows the results for the metropolitan area model and Table 35 shows the results for the non-metropolitan area model. The signs of the coefficients are as expected. Higher incomes, more vehicles, more drivers, and a greater freeway supply increase the average household DVMT. Owning no vehicles, living at higher population density, more public transit service, and living in an urban mixed-use area decrease the average household DVMT.

TABLE 34. METROPOLITAN AREA HOUSEHOLD AVERAGE DVMT MODEL

```
                        Estimate Std. Error  t value Pr(>|t|)    
(Intercept)            6.468e-01  2.882e-03  224.404  < 2e-16 ***
Census_rMidwest        7.168e-05  5.913e-04    0.121  0.90352    
Census_rSouth         -7.345e-04  4.812e-04   -1.526  0.12695    
Census_rWest           1.547e-03  5.900e-04    2.621  0.00876 ** 
LogIncome              1.073e-01  2.515e-04  426.739  < 2e-16 ***
Htppopdn              -3.160e-06  7.522e-08  -42.015  < 2e-16 ***
Hhvehcnt               5.797e-02  2.204e-04  263.031  < 2e-16 ***
ZeroVeh               -5.899e-01  7.509e-04 -785.642  < 2e-16 ***
Tranmilescap          -1.761e-04  2.043e-05   -8.619  < 2e-16 ***
Fwylnmicap             3.367e-02  1.209e-03   27.861  < 2e-16 ***
DrvAgePop              8.568e-02  2.416e-04  354.698  < 2e-16 ***
Age65Plus             -7.680e-02  2.723e-04 -281.995  < 2e-16 ***
Urban                 -6.126e-02  5.500e-04 -111.380  < 2e-16 ***
Htppopdn:Tranmilescap -1.154e-07  1.718e-09  -67.180  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02394 on 19475 degrees of freedom
Multiple R-squared: 0.9955,      Adjusted R-squared: 0.9955 
F-statistic: 3.334e+05 on 13 and 19475 DF,  p-value: < 2.2e-16
```

TABLE 35. NON-METROPOLITAN AREA HOUSEHOLD AVERAGE DVMT MODEL

```
                      Estimate Std. Error  t value Pr(>|t|)    
(Intercept)          8.217e-01  1.462e-03  562.070   <2e-16 ***
Census_rMidwest     -3.624e-04  2.520e-04   -1.438   0.1503    
Census_rSouth        6.064e-04  2.972e-04    2.040   0.0413 *  
Census_rWest         1.288e-04  3.479e-04    0.370   0.7112    
LogIncome            7.384e-02  1.439e-04  513.161   <2e-16 ***
Hhvehcnt             3.247e-02  1.040e-04  312.230   <2e-16 ***
ZeroVeh             -4.697e-01  5.355e-04 -877.139   <2e-16 ***
DrvAgePop            1.165e-02  6.275e-04   18.570   <2e-16 ***
Htppopdn            -5.796e-06  6.980e-08  -83.037   <2e-16 ***
Age0to14             8.958e-03  1.169e-04   76.605   <2e-16 ***
Age15to19            2.912e-02  6.618e-04   43.997   <2e-16 ***
Age20to29            8.952e-02  6.700e-04  133.608   <2e-16 ***
Age30to54            8.136e-02  6.569e-04  123.852   <2e-16 ***
Age55to64            7.402e-02  6.630e-04  111.640   <2e-16 ***
Age65Plus            2.386e-02  6.584e-04   36.243   <2e-16 ***
Htppopdn:Age20to29 -1.427e-06  4.925e-08  -28.981   <2e-16 ***
Htppopdn:Age30to54 -2.809e-06  4.217e-08  -66.624   <2e-16 ***
Htppopdn:Age55to64 -3.074e-06  5.785e-08  -53.147   <2e-16 ***
Htppopdn:Age65Plus -2.660e-06  5.276e-08  -50.413   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0175 on 35278 degrees of freedom
Multiple R-squared: 0.9921,      Adjusted R-squared: 0.9921 
F-statistic: 2.461e+05 on 18 and 35278 DF,  p-value: < 2.2e-16
```

Models were also developed to predict the 95th percentile and maximum DVMT values. These models were estimated as a function of the average household DVMT. Tables 36 and 37 show the estimation results for metropolitan area and non-metropolitan area households respectively. The terms in the models have the following meanings:

- DvmtAve – Average household DVMT
- DvmtAveSq – Square of average household DVMT
- DvmtAveCu – Cube of average household DVMT

TABLE 36. METROPOLITAN AREA HOUSEHOLD 95TH PERCENTILE AND MAXIMUM DVMT MODELS

95TH PERCENTILE DVMT MODEL

```
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  7.816e+00  1.018e-01   76.81   <2e-16 ***
DvmtAve      3.064e+00  4.627e-03  662.22   <2e-16 ***
DvmtAveSq   -7.589e-03  5.975e-05 -127.02   <2e-16 ***
DvmtAveCu    1.831e-05  2.059e-07   88.94   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.916 on 19485 degrees of freedom
Multiple R-squared: 0.9961,      Adjusted R-squared: 0.9961
F-statistic: 1.678e+06 on 3 and 19485 DF,  p-value: < 2.2e-16
```

MAXIMUM DVMT MODEL

```
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.001e+01  3.747e-01  133.48   <2e-16 ***
DvmtAve      5.279e+00  1.704e-02  309.89   <2e-16 ***
DvmtAveSq   -1.390e-02  2.200e-04  -63.20   <2e-16 ***
DvmtAveCu    3.069e-05  7.580e-07   40.48   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 18.1 on 19485 degrees of freedom
Multiple R-squared: 0.9816,      Adjusted R-squared: 0.9816
F-statistic: 3.463e+05 on 3 and 19485 DF,  p-value: < 2.2e-16
```

TABLE 37. NON-METROPOLITAN AREA HOUSEHOLD 95TH PERCENTILE AND MAXIMUM DVMT MODELS

95TH PERCENTILE DVMT MODEL

```
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.587e+01  9.308e-02  170.46   <2e-16 ***
DvmtAve      3.066e+00  2.696e-03 1137.50   <2e-16 ***
DvmtAveSq   -2.341e-03  1.974e-05 -118.60   <2e-16 ***
DvmtAveCu    1.619e-06  1.966e-08   82.35   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.786 on 35293 degrees of freedom
Multiple R-squared: 0.9953,      Adjusted R-squared: 0.9953
F-statistic: 2.504e+06 on 3 and 35293 DF,  p-value: < 2.2e-16
```

MAXIMUM DVMT MODEL

```
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  8.080e+01  4.556e-01  177.35   <2e-16 ***
DvmtAve      6.279e+00  1.319e-02  475.90   <2e-16 ***
DvmtAveSq   -6.882e-03  9.661e-05  -71.24   <2e-16 ***
DvmtAveCu    4.664e-06  9.624e-08   48.46   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 28.32 on 35293 degrees of freedom
Multiple R-squared: 0.9711,      Adjusted R-squared: 0.9711
F-statistic: 3.953e+05 on 3 and 35293 DF,  p-value: < 2.2e-16
```

Comparisons of the simulated and modeled distributions of average DVMT, 95th percentile DVMT, and maximum DVMT for the metropolitan area and non-metropolitan area households are shown in Figures 26 and 27 respectively.

FIGURE 26. COMPARISON OF SIMULATED AND ESTIMATED DISTRIBUTIONS OF AVERAGE DVMT, 95TH PERCENTILE DVMT, AND MAXIMUM DVMT FOR METROPOLITAN AREA HOUSEHOLDS

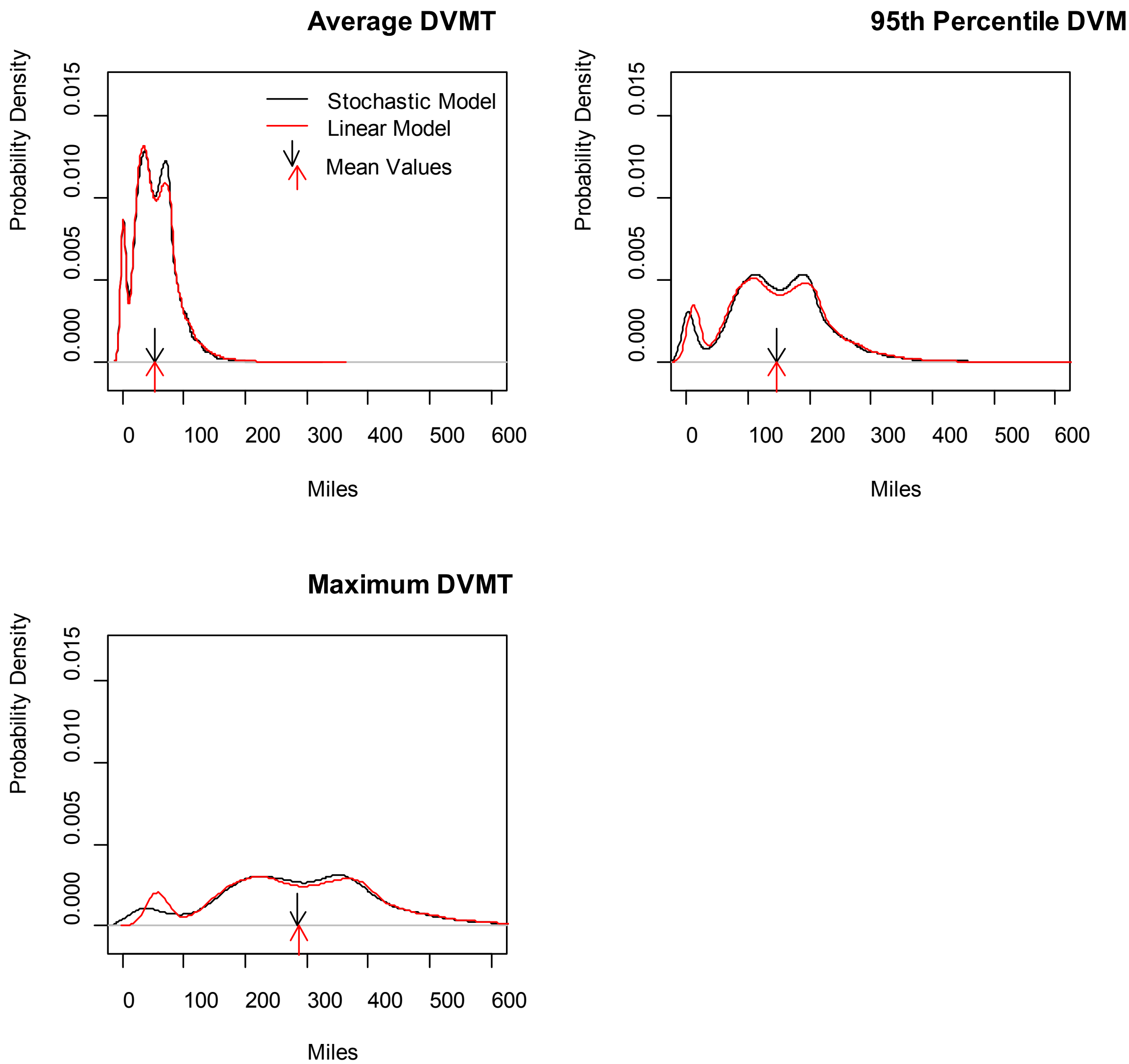
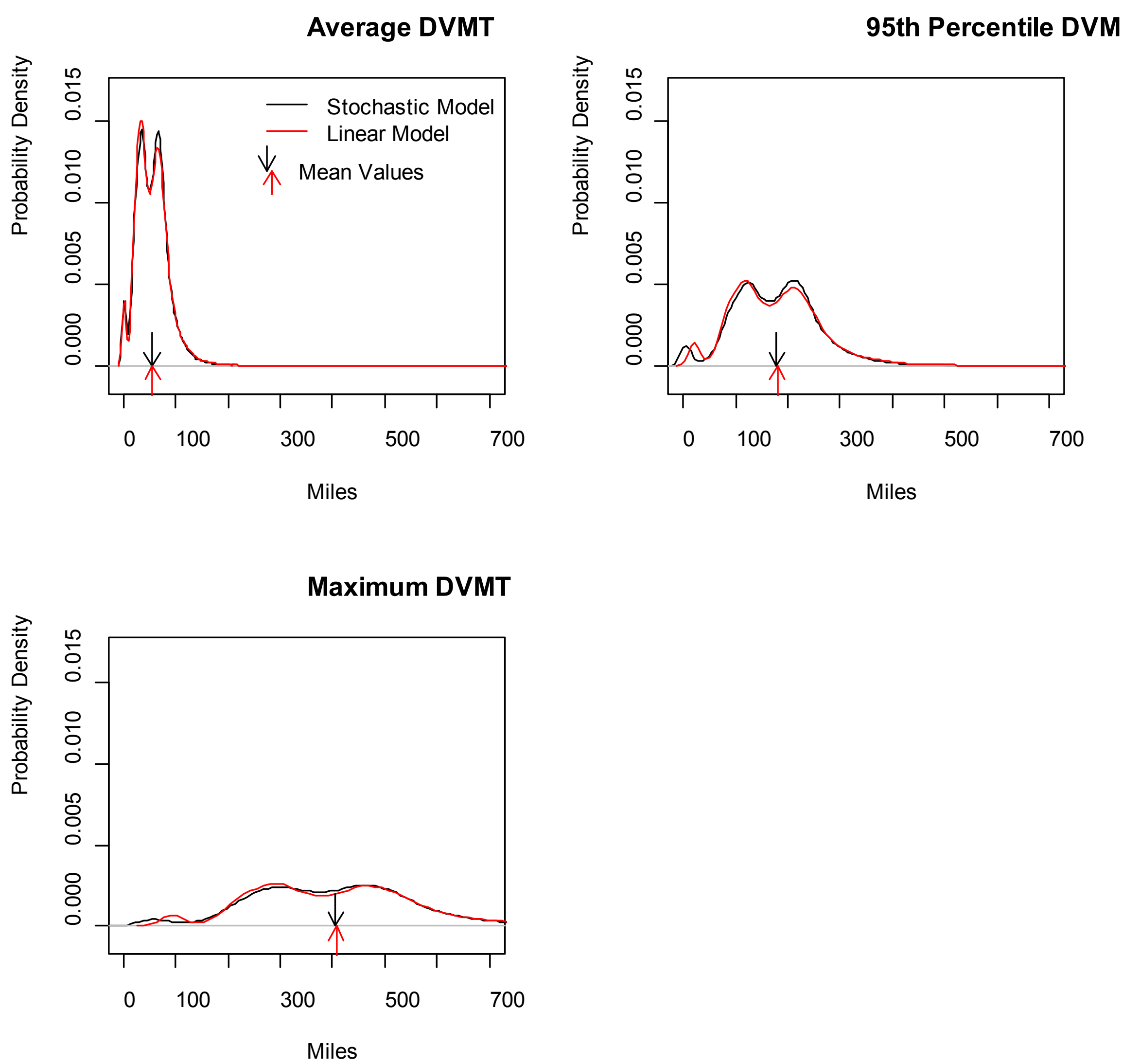


FIGURE 27. COMPARISON OF SIMULATED AND ESTIMATED DISTRIBUTIONS OF AVERAGE DVMT, 95TH PERCENTILE DVMT, AND MAXIMUM DVMT FOR NON-METROPOLITAN AREA HOUSEHOLDS



Calculate Non-Price TDM & Light Weight Vehicle Adjustment Factors & Adjust Household DVMT

TDM Adjustments

The average DVMT of households is adjusted based on their participation in ECO and/or IM programs. The default assumption is that that ECO programs reduce the average commute DVMT of participating households by 5.4%. This is based on assumptions used in the "Moving Cooler" study.[14] Because no satisfactory model could be found to distribute work DVMT between household members, it is assumed that all work travel of the household will be reduced by this percentage if any working age persons are identified as ECO participants. The reduction in total household DVMT is the percentage reduction in commute DVMT times the average commute percentage of total household DVMT (22%). It is assumed that households participating in an IM program reduce their DVMT by 9% based on studies done in the Portland area.[15] Since IM programs target work as well as non-work travel and since IM programs produce larger reductions, only the IM reduction is used for households that are identified as participating in both ECO and IM programs.

Light Weight Vehicles

Light-weight vehicles are bicycles, electric bicycles, Segways and similar vehicles that are small, light-weight and can travel at bicycle speeds or slightly higher than bicycle speeds. This class of vehicles, though currently a minor mode of urban transportation has the potential for having a large impact on transportation emissions in the future. Standard bicycles are the dominant form of light-weight vehicle in use in the United States. This may well change as electric bicycles and other light-weight electric vehicles grow in market share. Light-weight electric vehicles have the potential for substantially increasing light-weight vehicle travel because they reduce the difficulty and increase the convenience of this mode of travel. Technological improvements – lighter batteries and more efficient and powerful electric motors – are increasing the performance and reducing the costs of light-weight electric vehicles. Transportation system changes to accommodate light-weight vehicles (e.g. adding bike lanes) are increasing the convenience and safety of light-weight vehicle travel. These changes, along with increasing costs of gasoline and concerns about the impacts of vehicle travel could promote substantial increases in light weight vehicle travel in the future. An indication of the potential can be seen in the use of electric bicycles in China where it is estimated that up to 120 million are in use and where more than 1,000 companies manufacture electric bicycles.[16]

---

[14] Cambridge Systematics, "Moving Cooler", Urban Land Institute, Washington, D.C., 2009, Technical Appendix, Table 5.13, p. B-54.

[15] Insert reference.

[16] Joelle Garrus, Electric Bikes on a Roll in China, Agence France-Presse, 2/21/2010.

Modeling the potential future effect of light-weight vehicles is a challenge because of limited information about how people will use light-weight electric vehicles in U.S. cities and how the use of light-weight vehicles in general is affected by the availability of facilities. Given the challenge, the approach taken is to model the potential for diverting household DVMT to light vehicles rather than modeling the use of light vehicles. The core concept of the model is that light-weight vehicle usage will primarily be a substitute for short-distance single occupant vehicle (SOV) travel. Therefore the core component of the model is a model of the proportion of the household vehicle travel that occurs in short-distance SOV tours. This model determines the maximum potential for household DVMT to be diverted to light-weight vehicles given a specified tour length threshold.

The other factors that determine the total household DVMT that is diverted to light-vehicle travel are the proportion of households that have and use light vehicles and the proportion of SOV tours that light vehicles may be substituted for. A model is developed to predict the number of light vehicles owned by each household. This model is based on NHTS bicycle ownership data. The model is implemented with a function that allows the user to input an overall light vehicle ownership rate for the population. The proportion of SOV tours that light vehicles may be substituted for is a factor that reflects the effect of weather and trip purpose on limiting trips by light vehicles. This factor is multiplied by the potential DVMT that might be diverted by the household for households having light vehicles to calculate the DVMT that is diverted.

In order to develop the model of the proportion of household DVMT in short-distance SOV tours, the NHTS day trip data was used to tabulate each household's vehicle travel occurring in SOV tours having lengths less than or equal to distance thresholds of 2 miles, 5 miles, 10 miles, 15 miles and 20 miles. The proportion of the household's DVMT occurring at or less than these thresholds was then calculated. Exploratory data analysis reveals that the SOV proportions are related to household income, household size, household DVMT, population density, and urban mixed-use character.

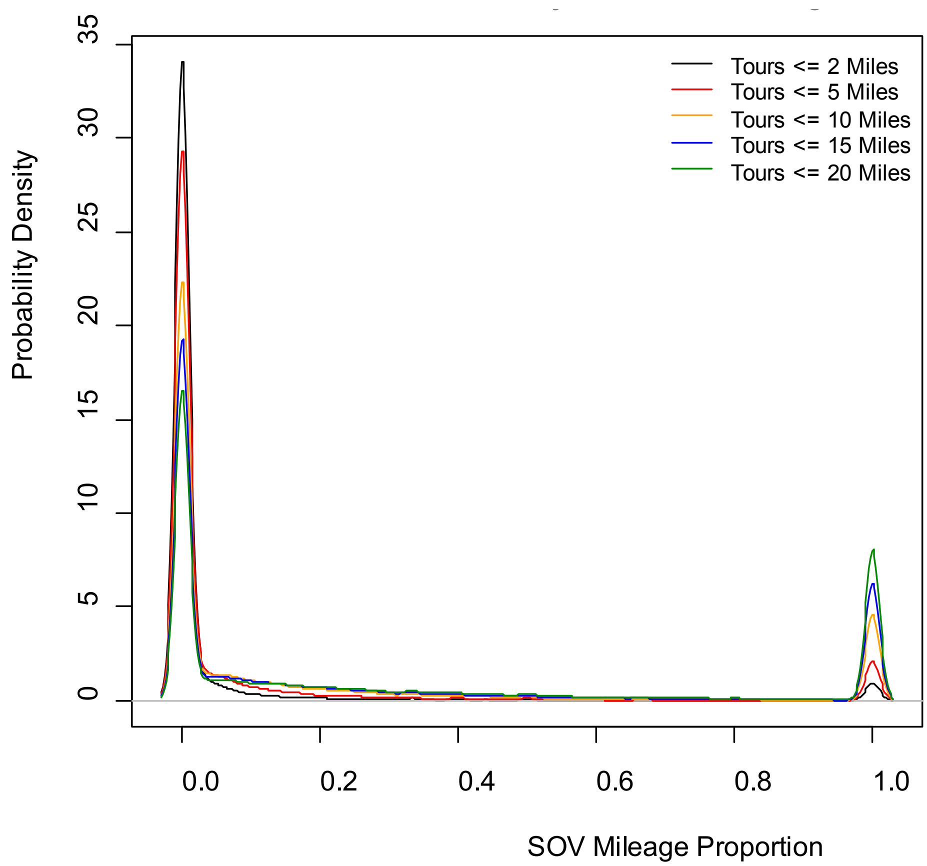
Because the tabulated SOV DVMT proportions represent the survey day results for the household rather than the averages for the household, a two stage process was used to develop a model. In the first stage, stochastic models were developed to predict the proportion of SOV travel that might occur on any given day. These models were then applied 100 times for each household to derive household averages. In the second stage of the process, linear models were estimated using the derived household averages.

Estimating a Stochastic Model of SOV Travel Proportions

Examination of the daily travel data reveals three groupings; households doing no SOV travel, households doing all SOV travel, and households doing some SOV travel. This is shown in Figure 28. It can be seen that most households are situated in clusters at the two ends of the distribution. This illustrates why a linear model should not be estimated directly from the data and why a two-stage model estimation process is necessary.

Three models were estimated for each SOV tour mileage threshold. Binomial models were estimated to predict the probability that a household had no SOV travel. Binomial models were also developed to predict the probability that a household had all of their travel in SOV tours. A linear model was estimated to predict the percentage of SOV travel for households that did some SOV travel but not all SOV travel. Tables 38 through 42 show the estimation results of the binomial models for predicting households doing no SOV travel for each mileage threshold. Tables 43 through 47 show the estimation results of the binomial models for households doing all SOV travel for each mileage threshold. Table 48 through 52 show the estimation results for linear models predicting the proportion of SOV travel for households doing some SOV travel but not all SOV travel for each mileage threshold.

FIGURE 28. DISTRIBUTION OF THE PROPORTION OF HOUSEHOLD DVMT IN SOV TOURS



The no-SOV, all-SOV and SOV proportion models were applied sequentially to determine the proportion of SOV travel for a household on any given day. First, the no-SOV model was applied to determine which of the households had any SOV travel on the day. Then the all SOV model was applied to determine whether households that had any SOV had only SOV travel. Finally the SOV proportion model is applied to households that had neither SOV travel nor all SOV travel to determine the proportion of SOV travel for the day. This process was repeated 100 times for all households.

TABLE 38. ESTIMATION OF RESULTS FOR BINOMIAL MODEL OF THE PROBABILITY OF NO SOV TRAVEL WITHIN A DISTANCE THRESHOLD OF 2 MILES

```
                  Estimate Std. Error z value Pr(>|z|)    
(Intercept)     -4.202e-01  6.053e-02  -6.941 3.88e-12 ***
LogSize          1.188e+00  9.658e-02  12.301  < 2e-16 ***
Urban           -1.651e+00  5.761e-01  -2.867 0.004149 ** 
LogDvmt          7.551e-01  2.061e-02  36.633  < 2e-16 ***
LogSize:LogDvmt -3.162e-01  2.080e-02 -15.202  < 2e-16 ***
LogSize:LogDen  -7.593e-02  8.420e-03  -9.017  < 2e-16 ***
Urban:LogDen     2.312e-01  6.176e-02   3.743 0.000182 ***
Urban:Hhincttl  -5.732e-06  1.289e-06  -4.447 8.71e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 38132  on 45132  degrees of freedom
Residual deviance: 35869  on 45125  degrees of freedom
AIC: 35885

Number of Fisher Scoring iterations: 5
```

TABLE 39. ESTIMATION RESULTS FOR BINOMIAL MODEL OF THE PROBABILITY OF NO SOV TRAVEL WITHIN A DISTANCE THRESHOLD OF 5 MILES

```
                  Estimate Std. Error z value Pr(>|z|)    
(Intercept)     -1.328e+00  5.946e-02 -22.337  < 2e-16 ***
LogSize          1.384e+00  1.187e-01  11.660  < 2e-16 ***
Hhincttl        -1.543e-06  3.773e-07  -4.090 4.32e-05 ***
Urban           -2.336e+00  5.062e-01  -4.614 3.94e-06 ***
LogDvmt          9.157e-01  2.950e-02  31.038  < 2e-16 ***
LogDvmt:LogDen  -2.054e-02  3.570e-03  -5.753 8.79e-09 ***
LogSize:LogDvmt -3.592e-01  1.861e-02 -19.305  < 2e-16 ***
Urban:LogDvmt    6.802e-02  3.626e-02   1.876   0.0607 .  
LogSize:LogDen  -5.919e-02  1.278e-02  -4.633 3.60e-06 ***
Urban:LogDen     2.817e-01  5.216e-02   5.402 6.59e-08 ***
Hhincttl:Urban  -2.823e-06  1.180e-06  -2.392   0.0167 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 52595  on 45132  degrees of freedom
Residual deviance: 49176  on 45122  degrees of freedom
AIC: 49198

Number of Fisher Scoring iterations: 4
```

TABLE 40. ESTIMATION RESULTS FOR BINOMIAL MODEL OF THE PROBABILITY OF NO SOV TRAVEL WITHIN A DISTANCE THRESHOLD OF 10 MILES

```
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)     -2.260e+00  6.273e-02 -36.022  < 2e-16 ***
LogSize          1.685e+00  1.101e-01  15.312  < 2e-16 ***
Hhincttl        -2.975e-06  3.360e-07  -8.854  < 2e-16 ***
Urban           -3.455e+00  4.766e-01  -7.249 4.20e-13 ***
LogDvmt          9.646e-01  2.607e-02  37.008  < 2e-16 ***
LogDvmt:LogDen  -2.658e-02  3.019e-03  -8.805  < 2e-16 ***
LogSize:LogDvmt -4.284e-01  1.815e-02 -23.605  < 2e-16 ***
Urban:LogDvmt    1.080e-01  3.520e-02   3.067 0.002162 **
LogSize:LogDen  -4.146e-02  1.124e-02  -3.687 0.000227 ***
Urban:LogDen     3.984e-01  4.853e-02   8.210  < 2e-16 ***
Hhincttl:Urban  -2.564e-06  1.089e-06  -2.355 0.018529 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 61998  on 45132  degrees of freedom
Residual deviance: 58225  on 45122  degrees of freedom
AIC: 58247

Number of Fisher Scoring iterations: 4
```

TABLE 41. ESTIMATION RESULTS FOR BINOMIAL MODEL OF THE PROBABILITY OF NO SOV TRAVEL WITHIN A DISTANCE THRESHOLD OF 15 MILES

```
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)     -2.670e+00  6.520e-02 -40.961  < 2e-16 ***
LogSize          1.805e+00  1.097e-01  16.449  < 2e-16 ***
Hhincttl        -3.585e-06  3.326e-07 -10.779  < 2e-16 ***
Urban           -2.802e+00  4.466e-01  -6.275 3.50e-10 ***
LogDvmt          9.495e-01  2.560e-02  37.098  < 2e-16 ***
LogDvmt:LogDen  -2.364e-02  2.851e-03  -8.292  < 2e-16 ***
LogSize:LogDvmt -4.414e-01  1.853e-02 -23.815  < 2e-16 ***
LogSize:LogDen  -3.579e-02  1.089e-02  -3.287  0.00101 **
Urban:LogDen     3.628e-01  4.764e-02   7.614 2.65e-14 ***
Hhincttl:Urban  -2.309e-06  1.045e-06  -2.209  0.02714 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 62485  on 45132  degrees of freedom
Residual deviance: 58921  on 45123  degrees of freedom
AIC: 58941

Number of Fisher Scoring iterations: 4
```

TABLE 42. ESTIMATION RESULTS FOR BINOMIAL MODEL OF THE PROBABILITY OF NO SOV TRAVEL WITHIN A DISTANCE THRESHOLD OF 20 MILES

```
                   Estimate Std. Error z value Pr(>|z|)    
(Intercept)      -2.815e+00  7.986e-02 -35.246  < 2e-16 ***
LogSize           1.995e+00  1.133e-01  17.605  < 2e-16 ***
Hhincttl         -7.802e-06  1.203e-06  -6.485 8.88e-11 ***
Urban            -2.503e+00  4.495e-01  -5.568 2.58e-08 ***
LogDvmt           9.072e-01  2.800e-02  32.395  < 2e-16 ***
LogDvmt:LogDen   -2.390e-02  2.814e-03  -8.493  < 2e-16 ***
LogSize:LogDvmt  -4.921e-01  1.976e-02 -24.908  < 2e-16 ***
Hhincttl:LogDvmt  8.266e-07  3.052e-07   2.709  0.00676 ** 
LogSize:LogDen   -2.298e-02  1.083e-02  -2.121  0.03393 *  
Urban:LogDen      3.169e-01  4.826e-02   6.567 5.14e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 61130  on 45132  degrees of freedom
Residual deviance: 58004  on 45123  degrees of freedom
AIC: 58024

Number of Fisher Scoring iterations: 4
```

TABLE 43. ESTIMATION RESULTS FOR BINOMIAL MODEL OF THE PROBABILITY OF AL TRAVEL BY SOV IN DISTANCE THRESHOLD OF 2 MILES

```
                  Estimate Std. Error z value Pr(>|z|)    
(Intercept)        5.90298    0.26256  22.482  < 2e-16 ***
LogDvmt           -3.58676    0.26955 -13.306  < 2e-16 ***
LogDvmt:LogDen    -0.13423    0.03238  -4.146 3.39e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5781.52  on 6762  degrees of freedom
Residual deviance:  975.05  on 6760  degrees of freedom
AIC: 981.05

Number of Fisher Scoring iterations: 9
```

TABLE 44. ESTIMATION RESULTS FOR BINOMIAL MODEL OF THE PROBABILITY OF ALL TRAVEL BY SOV IN DISTANCE THRESHOLD OF 5 MILES

```
                   Estimate Std. Error z value Pr(>|z|)    
(Intercept)       6.821e+00  7.865e-01   8.672  < 2e-16 ***
LogDen            3.118e-01  1.031e-01   3.024  0.00249 ** 
LogSize          -3.097e+00  3.576e-01  -8.660  < 2e-16 ***
Hhincttl          3.886e-06  1.736e-06   2.239  0.02517 *  
LogDvmt          -3.097e+00  3.889e-01  -7.964 1.67e-15 ***
LogDen:LogDvmt   -2.036e-01  5.119e-02  -3.977 6.97e-05 ***
LogSize:LogDvmt   9.814e-01  1.781e-01   5.509 3.60e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 11947.1  on 12158  degrees of freedom
Residual deviance:  2775.4  on 12152  degrees of freedom
AIC: 2789.4

Number of Fisher Scoring iterations: 8
```

TABLE 45. ESTIMATION RESULTS FOR BINOMIAL MODEL OF THE PROBABILITY OF ALL TRAVEL BY SOV IN DISTANCE THRESHOLD OF 10 MILES

```
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)       8.946e+00  2.941e-01  30.420  < 2e-16 ***
LogSize          -3.416e+00  2.535e-01 -13.476  < 2e-16 ***
Hhincttl          1.597e-05  4.483e-06   3.563 0.000367 ***
LogDvmt          -3.330e+00  1.103e-01 -30.188  < 2e-16 ***
LogSize:LogDvmt   7.966e-01  9.627e-02   8.275  < 2e-16 ***
Hhincttl:LogDvmt -5.222e-06  1.665e-06  -3.137 0.001708 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 22945  on 20034  degrees of freedom
Residual deviance:  8179  on 20029  degrees of freedom
AIC: 8191

Number of Fisher Scoring iterations: 7
```

TABLE 46. ESTIMATION RESULTS FOR BINOMIAL MODEL OF THE PROBABILITY OF ALL TRAVEL BY SOV IN DISTANCE THRESHOLD OF 15 MILES

```
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)       9.851e+00  5.680e-01  17.342  < 2e-16 ***
LogDen           -1.693e-01  7.013e-02  -2.414  0.01580 *
LogSize          -2.836e+00  3.239e-01  -8.757  < 2e-16 ***
Hhincttl          1.760e-05  3.764e-06   4.677 2.91e-06 ***
LogDvmt          -3.326e+00  1.805e-01 -18.429  < 2e-16 ***
LogDen:LogDvmt    6.480e-02  2.225e-02   2.913  0.00358 **
LogSize:LogDvmt   6.765e-01  7.554e-02   8.956  < 2e-16 ***
Hhincttl:LogDvmt -5.102e-06  1.255e-06  -4.064 4.82e-05 ***
LogDen:LogSize   -8.482e-02  3.046e-02  -2.784  0.00537 **
LogSize:Urban     4.140e-01  1.490e-01   2.778  0.00546 **
Hhincttl:Urban   -4.207e-06  1.949e-06  -2.159  0.03086 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 28897  on 23532  degrees of freedom
Residual deviance: 12280  on 23522  degrees of freedom
AIC: 12302

Number of Fisher Scoring iterations: 7
```

TABLE 47. ESTIMATION RESULTS FOR BINOMIAL MODEL OF THE PROBABILITY OF ALL TRAVEL BY SOV IN DISTANCE THRESHOLD OF 20 MILES

```
                    Estimate Std. Error z value Pr(>|z|)    
(Intercept)        9.980e+00  4.877e-01  20.461  < 2e-16 ***
LogDen            -2.688e-01  5.941e-02  -4.525 6.05e-06 ***
LogSize           -2.833e+00  2.805e-01 -10.100  < 2e-16 ***
Hhincttl           1.622e-05  3.155e-06   5.139 2.76e-07 ***
LogDvmt           -2.989e+00  1.431e-01 -20.879  < 2e-16 ***
LogDen:LogDvmt     8.021e-02  1.748e-02   4.588 4.48e-06 ***
LogSize:LogDvmt    5.693e-01  6.144e-02   9.267  < 2e-16 ***
Hhincttl:LogDvmt -4.703e-06  9.832e-07  -4.783 1.72e-06 ***
LogDen:LogSize    -6.662e-02  2.515e-02  -2.649  0.00807 ** 
LogSize:Urban      2.393e-01  8.574e-02   2.791  0.00526 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 34233  on 26583  degrees of freedom
Residual deviance: 16880  on 26574  degrees of freedom
AIC: 16900

Number of Fisher Scoring iterations: 6
```

TABLE 48. ESTIMATION RESULTS FOR LINEAR MODEL OF THE PROPORTION OF HOUSEHOLD DVMT IN SOV TOURS LESS THAN OR EQUAL TO 2 MILES

```
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)        5.232e-01  9.984e-03  52.404  < 2e-16 ***
LogDen            -3.351e-03  6.503e-04  -5.153 2.65e-07 ***
LogSize           -5.369e-02  8.241e-03  -6.515 7.91e-11 ***
Hhincttl          -5.225e-07  1.370e-07  -3.813 0.000139 ***
LogDvmt           -1.234e-01  2.761e-03 -44.695  < 2e-16 ***
LogSize:LogDvmt    2.178e-02  2.310e-03   9.428  < 2e-16 ***
Hhincttl:LogDvmt   2.428e-07  3.667e-08   6.622 3.87e-11 ***
LogSize:Hhincttl -2.881e-07  7.661e-08  -3.760 0.000171 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.08302 on 5722 degrees of freedom
Multiple R-squared: 0.5486,   Adjusted R-squared: 0.5481
F-statistic: 993.5 on 7 and 5722 DF,  p-value: < 2.2e-16
```

TABLE 49. ESTIMATION RESULTS FOR LINEAR MODEL OF THE PROPORTION OF HOUSEHOLD DVMT IN SOV TOURS LESS THAN OR EQUAL TO 5 MILES

```
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)          4.937e-01  2.157e-02  22.886  < 2e-16 ***
LogDen               1.935e-02  2.657e-03   7.282 3.54e-13 ***
LogSize             -3.815e-02  9.419e-03  -4.050 5.15e-05 ***
Hhincttl            -4.945e-07  1.485e-07  -3.329 0.000874 ***
Urban               -1.587e-02  4.320e-03  -3.673 0.000241 ***
LogDvmt             -1.103e-01  5.775e-03 -19.095  < 2e-16 ***
LogDen:LogDvmt      -4.802e-03  6.926e-04  -6.933 4.37e-12 ***
LogSize:LogDvmt      1.756e-02  2.601e-03   6.752 1.54e-11 ***
Hhincttl:LogDvmt     2.269e-07  3.851e-08   5.891 3.96e-09 ***
LogSize:Hhincttl    -2.724e-07  7.534e-08  -3.616 0.000301 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1077 on 9796 degrees of freedom
Multiple R-squared: 0.4905,    Adjusted R-squared:  0.49 
F-statistic:  1048 on 9 and 9796 DF,  p-value: < 2.2e-16
```

TABLE 50. ESTIMATION RESULTS FOR LINEAR MODEL OF THE PROPORTION OF HOUSEHOLD DVMT IN SOV TOURS LESS THAN OR EQUAL TO 10 MILES

```
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)          5.416e-01  2.448e-02  22.123  < 2e-16 ***
LogDen               2.482e-02  3.349e-03   7.413 1.30e-13 ***
LogSize              2.395e-02  5.013e-03   4.777 1.79e-06 ***
Urban                1.828e-01  5.784e-02   3.160 0.001583 ** 
LogDvmt             -1.063e-01  6.195e-03 -17.154  < 2e-16 ***
LogDen:LogDvmt      -5.378e-03  8.393e-04  -6.408 1.52e-10 ***
LogDvmt:Hhincttl     1.016e-07  2.129e-08   4.773 1.83e-06 ***
LogSize:Hhincttl    -1.826e-07  7.934e-08  -2.302 0.021374 *  
LogDen:Urban        -2.273e-02  6.300e-03  -3.609 0.000309 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1461 on 14825 degrees of freedom
Multiple R-squared: 0.384,     Adjusted R-squared: 0.3837 
F-statistic:  1155 on 8 and 14825 DF,  p-value: < 2.2e-16
```

TABLE 51. ESTIMATION RESULTS FOR LINEAR MODEL OF THE PROPORTION OF HOUSEHOLD DVMT IN SOV TOURS LESS THAN OR EQUAL TO 15 MILES

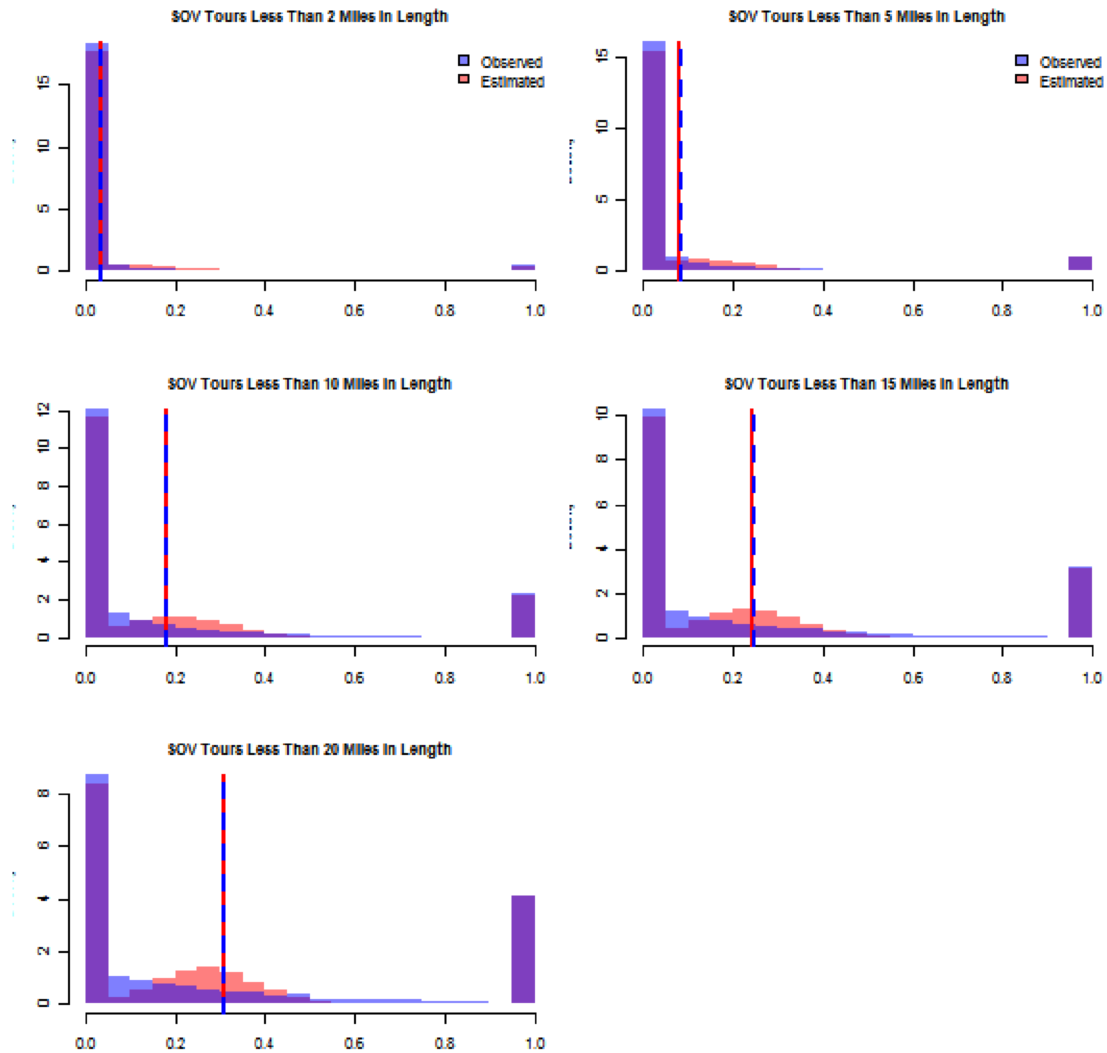
```
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)       6.102e-01  2.942e-02  20.740  < 2e-16 ***
LogDen            1.812e-02  3.813e-03   4.752 2.03e-06 ***
LogSize           1.794e-02  2.965e-03   6.051 1.47e-09 ***
Hhincttl          9.239e-07  1.940e-07   4.763 1.92e-06 ***
Urban             2.457e-01  6.581e-02   3.734 0.000189 ***
LogDvmt          -1.114e-01  7.239e-03 -15.382  < 2e-16 ***
LogDen:LogDvmt   -3.818e-03  9.414e-04  -4.056 5.02e-05 ***
Hhincttl:LogDvmt -1.470e-07  4.839e-08  -3.038 0.002389 ** 
LogDen:Urban     -2.810e-02  7.157e-03  -3.926 8.66e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1682 on 16377 degrees of freedom
Multiple R-squared: 0.3335,   Adjusted R-squared: 0.3332 
F-statistic:  1024 on 8 and 16377 DF,  p-value: < 2.2e-16
```

TABLE 52. ESTIMATION RESULTS FOR LINEAR MODEL OF THE PROPORTION OF HOUSEHOLD DVMT IN SOV TOURS LESS THAN OR EQUAL TO 20 MILES

```
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)       6.844e-01  2.060e-02  33.227  < 2e-16 ***
LogDen            7.415e-03  1.790e-03   4.143 3.44e-05 ***
LogSize           2.700e-02  3.260e-03   8.284  < 2e-16 ***
Hhincttl          2.118e-06  3.091e-07   6.852 7.53e-12 ***
Urban             2.494e-01  7.421e-02   3.360 0.000780 ***
LogDvmt          -1.288e-01  3.696e-03 -34.837  < 2e-16 ***
Hhincttl:LogDvmt -2.997e-07  5.377e-08  -5.574 2.52e-08 ***
LogDen:Hhincttl  -7.825e-08  2.666e-08  -2.935 0.003344 ** 
LogDen:Urban     -2.792e-02  8.056e-03  -3.465 0.000531 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1895 on 17421 degrees of freedom
Multiple R-squared: 0.2813,   Adjusted R-squared: 0.281 
F-statistic: 852.4 on 8 and 17421 DF,  p-value: < 2.2e-16
```

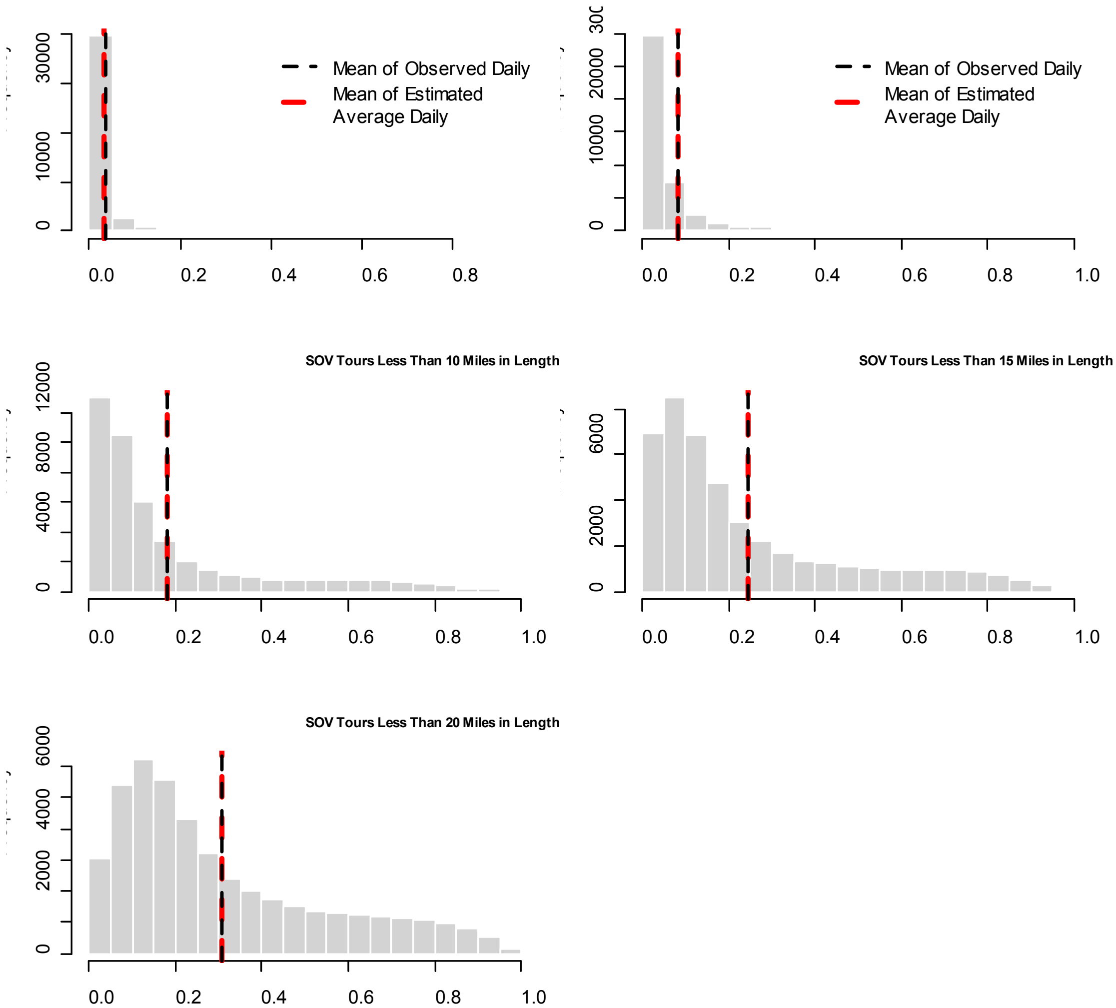
Figure 29 compares the observed household distributions of SOV proportions of household DVMT with the modeled proportions. Observed and estimated mean values are very close. The model does very well at modeling the all-SOV component. It slightly under predicts the no-SOV component. It does less well at modeling the middle of the distribution because the model produces a normal distribution whereas the observed distribution is not normal.

FIGURE 29. OBSERVED AND MODELED DAILY DISTRIBUTIONS OF THE PROPORTIONS OF HOUSEHOLD DVMT IN TOURS OF VARIOUS LENGTHS



Average SOV proportions for each household and for each mileage threshold were estimated by applying the set of models for each mileage threshold 100 times and averaging the results. Figure 30 shows the distributions of the resulting estimates. The means of the estimated average values are very close to the means of the observed values.

FIGURE 30. DISTRIBUTION OF AVERAGE PROPORTIONS OF HOUSEHOLD DVMT IN SOV TOURS BY MAXIMUM TOUR LENGTH



Once the average proportions had been calculated for each household through simulation, linear models were estimated to predict the averages. Tables 53 through 57 show the estimation statistics for the models.

TABLE 53. ESTIMATION RESULTS FOR LINEAR MODEL OF THE PROBABILITY OF HOUSEHOLD DVMT IN SOV TOURS LESS THAN OR EQUAL TO 2 MILES

```
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)        3.301e-01  3.957e-03  83.415  < 2e-16 ***
Hhincttl          -1.317e-06  4.796e-08 -27.468  < 2e-16 ***
LogDen             2.709e-03  5.190e-04   5.219 1.81e-07 ***
LogSize           -1.255e-01  2.802e-03 -44.794  < 2e-16 ***
Urban              3.106e-02  1.164e-02   2.668 0.007636 ** 
LogDvmt           -7.445e-02  1.029e-03 -72.371  < 2e-16 ***
Hhincttl:LogDvmt   3.633e-07  7.290e-09  49.833  < 2e-16 ***
LogDen:LogDvmt    -3.131e-03  1.373e-04 -22.801  < 2e-16 ***
LogSize:LogDvmt    3.094e-02  4.509e-04  68.611  < 2e-16 ***
Urban:LogDvmt     -3.341e-03  8.750e-04  -3.818 0.000135 ***
Hhincttl:LogDen    3.905e-08  5.019e-09   7.780 7.40e-15 ***
Hhincttl:LogSize -2.779e-07  1.650e-08 -16.844  < 2e-16 ***
Hhincttl:Urban     2.356e-07  2.982e-08   7.899 2.87e-15 ***
LogDen:LogSize     5.305e-03  2.869e-04  18.491  < 2e-16 ***
LogDen:Urban      -4.058e-03  1.200e-03  -3.383 0.000719 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 

Residual standard error: 0.05228 on 45118 degrees of freedom
Multiple R-squared: 0.6111,	Adjusted R-squared: 0.611 
F-statistic:  5064 on 14 and 45118 DF,  p-value: < 2.2e-16
```

TABLE 54. ESTIMATION RESULTS FOR LINEAR MODEL OF THE PROPORTION OF HOUSEHOLD DVMT IN SOV TOURS LESS THAN OR EQUAL TO 5 MILES

```
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)        5.315e-01  4.982e-03 106.689  < 2e-16 ***
Hhincttl          -1.246e-06  6.196e-08 -20.113  < 2e-16 ***
LogDen             1.916e-02  6.376e-04  30.046  < 2e-16 ***
LogSize           -2.652e-01  3.625e-03 -73.155  < 2e-16 ***
Urban              8.884e-02  1.453e-02   6.116 9.65e-10 ***
LogDvmt           -1.221e-01  1.271e-03 -96.089  < 2e-16 ***
Hhincttl:LogDvmt   3.915e-07  9.431e-09  41.509  < 2e-16 ***
LogDen:LogDvmt    -7.400e-03  1.623e-04 -45.600  < 2e-16 ***
LogSize:LogDvmt    6.490e-02  5.833e-04 111.268  < 2e-16 ***
Hhincttl:LogDen    4.258e-08  6.461e-09   6.590 4.46e-11 ***
Hhincttl:LogSize -3.884e-07  2.134e-08 -18.200  < 2e-16 ***
Hhincttl:Urban     2.945e-07  3.746e-08   7.861 3.89e-15 ***
LogDen:LogSize     7.318e-03  3.710e-04  19.725  < 2e-16 ***
LogDen:Urban      -1.330e-02  1.550e-03  -8.581  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 

Residual standard error: 0.06764 on 45119 degrees of freedom
Multiple R-squared:  0.78,	Adjusted R-squared:  0.78 
F-statistic: 1.231e+04 on 13 and 45119 DF,  p-value: < 2.2e-16
```

TABLE 55. ESTIMATION RESULTS FOR LINEAR MODEL OF THE PROPORTION OF HOUSEHOLD DVMT IN SOV TOURS LESS THAN OR EQUAL TO 10 MILES

```
                    Estimate Std. Error  t value Pr(>|t|)    
(Intercept)        7.786e-01  5.135e-03  151.625  < 2e-16 ***
Hhincttl          -1.538e-07  6.225e-08   -2.471 0.013473 *  
LogDen             3.303e-02  6.739e-04   49.019  < 2e-16 ***
LogSize           -3.590e-01  3.738e-03  -96.038  < 2e-16 ***
Urban              3.322e-01  1.509e-02   22.007  < 2e-16 ***
LogDvmt           -1.791e-01  1.338e-03 -133.802  < 2e-16 ***
Hhincttl:LogDvmt   1.585e-07  9.454e-09   16.764  < 2e-16 ***
LogDen:LogDvmt    -8.185e-03  1.791e-04  -45.706  < 2e-16 ***
LogSize:LogDvmt    8.624e-02  5.848e-04  147.472  < 2e-16 ***
Urban:LogDvmt      4.186e-03  1.155e-03    3.624 0.000291 ***
Hhincttl:LogDen    1.483e-08  6.536e-09    2.269 0.023262 *  
Hhincttl:LogSize  -2.408e-07  2.139e-08  -11.256  < 2e-16 ***
Hhincttl:Urban     3.658e-07  3.952e-08    9.257  < 2e-16 ***
LogDen:LogSize     4.352e-03  4.077e-04   10.673  < 2e-16 ***
LogDen:Urban      -4.480e-02  1.557e-03  -28.773  < 2e-16 ***
LogSize:Urban      5.090e-03  2.495e-03    2.040 0.041336 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.06779 on 45117 degrees of freedom
Multiple R-squared: 0.8963,     Adjusted R-squared: 0.8962 
F-statistic: 2.599e+04 on 15 and 45117 DF,  p-value: < 2.2e-16
```

TABLE 56. ESTIMATION RESULTS FOR LINEAR MODEL OF THE PROPORTION OF HOUSEHOLD DVMT IN SOV TOURS LESS THAN OR EQUAL TO 15 MILES

```
                    Estimate Std. Error  t value Pr(>|t|)    
(Intercept)        9.364e-01  4.685e-03  199.893  < 2e-16 ***
Hhincttl           7.014e-07  3.424e-08   20.483  < 2e-16 ***
LogDen             2.743e-02  6.171e-04   44.444  < 2e-16 ***
LogSize           -3.657e-01  2.023e-03 -180.792  < 2e-16 ***
Urban              3.388e-01  1.446e-02   23.428  < 2e-16 ***
LogDvmt           -2.086e-01  1.228e-03 -169.879  < 2e-16 ***
Hhincttl:LogDvmt  -6.511e-08  8.747e-09   -7.444 9.95e-14 ***
LogDen:LogDvmt    -5.102e-03  1.615e-04  -31.602  < 2e-16 ***
LogSize:LogDvmt    8.572e-02  5.408e-04  158.515  < 2e-16 ***
Urban:LogDvmt      1.516e-02  1.097e-03   13.821  < 2e-16 ***
Hhincttl:Urban     2.329e-07  3.450e-08    6.751 1.49e-11 ***
LogDen:Urban      -5.025e-02  1.493e-03  -33.661  < 2e-16 ***
LogSize:Urban      1.662e-02  2.183e-03    7.614 2.71e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.06505 on 45120 degrees of freedom
Multiple R-squared: 0.9223,     Adjusted R-squared: 0.9223 
F-statistic: 4.462e+04 on 12 and 45120 DF,  p-value: < 2.2e-16
```

TABLE 57. ESTIMATION RESULTS FOR LINEAR MODEL OF THE PROPORTION OF HOUSEHOLD DVMT IN SOV TOURS LESS THAN OR EQUAL TO 20 MILES

```
                     Estimate Std. Error  t value Pr(>|t|)    
(Intercept)         1.038e+00  4.714e-03  220.281  < 2e-16 ***
Hhincttl            2.232e-06  5.714e-08   39.053  < 2e-16 ***
LogDen              1.847e-02  6.186e-04   29.864  < 2e-16 ***
LogSize            -3.745e-01  3.432e-03 -109.122  < 2e-16 ***
Urban               3.461e-01  1.386e-02   24.981  < 2e-16 ***
LogDvmt            -2.238e-01  1.228e-03 -182.199  < 2e-16 ***
Hhincttl:LogDvmt -3.846e-07  8.679e-09  -44.314  < 2e-16 ***
LogDen:LogDvmt     -9.628e-04  1.644e-04   -5.857 4.73e-09 ***
LogSize:LogDvmt     8.333e-02  5.368e-04  155.237  < 2e-16 ***
Urban:LogDvmt       1.639e-02  1.060e-03   15.454  < 2e-16 ***
Hhincttl:LogDen    -5.608e-08  6.000e-09   -9.346  < 2e-16 ***
Hhincttl:LogSize    2.147e-07  1.964e-08   10.933  < 2e-16 ***
Hhincttl:Urban      1.434e-07  3.628e-08    3.953 7.73e-05 ***
LogDen:LogSize     -2.771e-03  3.743e-04   -7.405 1.33e-13 ***
LogDen:Urban       -5.036e-02  1.429e-03  -35.237  < 2e-16 ***
LogSize:Urban       1.075e-02  2.290e-03    4.695 2.68e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06223 on 45117 degrees of freedom
Multiple R-squared: 0.9337,     Adjusted R-squared: 0.9337 
F-statistic: 4.236e+04 on 15 and 45117 DF,  p-value: < 2.2e-16
```

One problem with linear models of proportions is that the results are not limited to the range of 0 to 1. Some results are negative or greater than one. This can be corrected by applying a logistic transform to the results. This constrains the results within the bounds of 0 and 1. It also improves the model fit. The form of the logistic function is as follows:

$$\text{PropTransform} = \frac{1}{1+\exp(-\alpha \bullet (\text{PropModel} - \beta))} - (0.5 - \beta)$$

The alpha and beta parameters of the transform were estimated by iterating over sequences of values to find the parameters that produced the best fit. Two statistics were used to assess the degree of fit:

- Correlation between the observed and the transformed model estimates
- Difference in the observed and transformed model mean values

Parameters were chosen that maximized the correlation and minimized the difference in the mean values.

Parameters were estimated for each mileage threshold model. Figure 31 shows scatterplots comparing the simulated and modeled values with and without the logistic transforms. The black dots show the comparison without the logistic transform. The red dots compare the results with the logistic transform. It can be seen that the transformation produces values in the acceptable range and improves the model fit.

FIGURE 31. COMPARISON ON MODELED AND SIMULATED SOV TRAVEL PROPORTIONS WITH AND WITHOUT LOGISTIC TRANSFORMATION

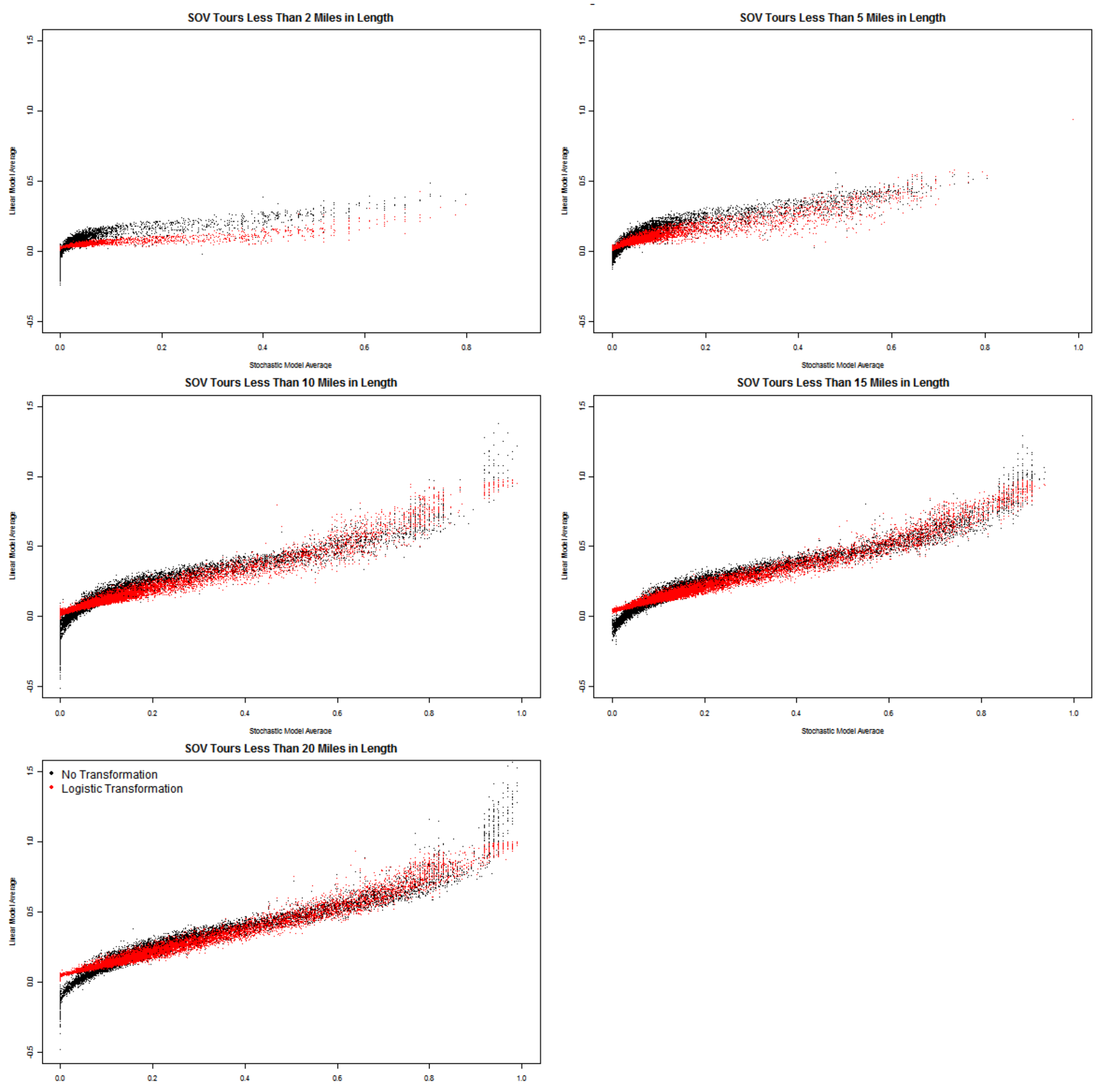
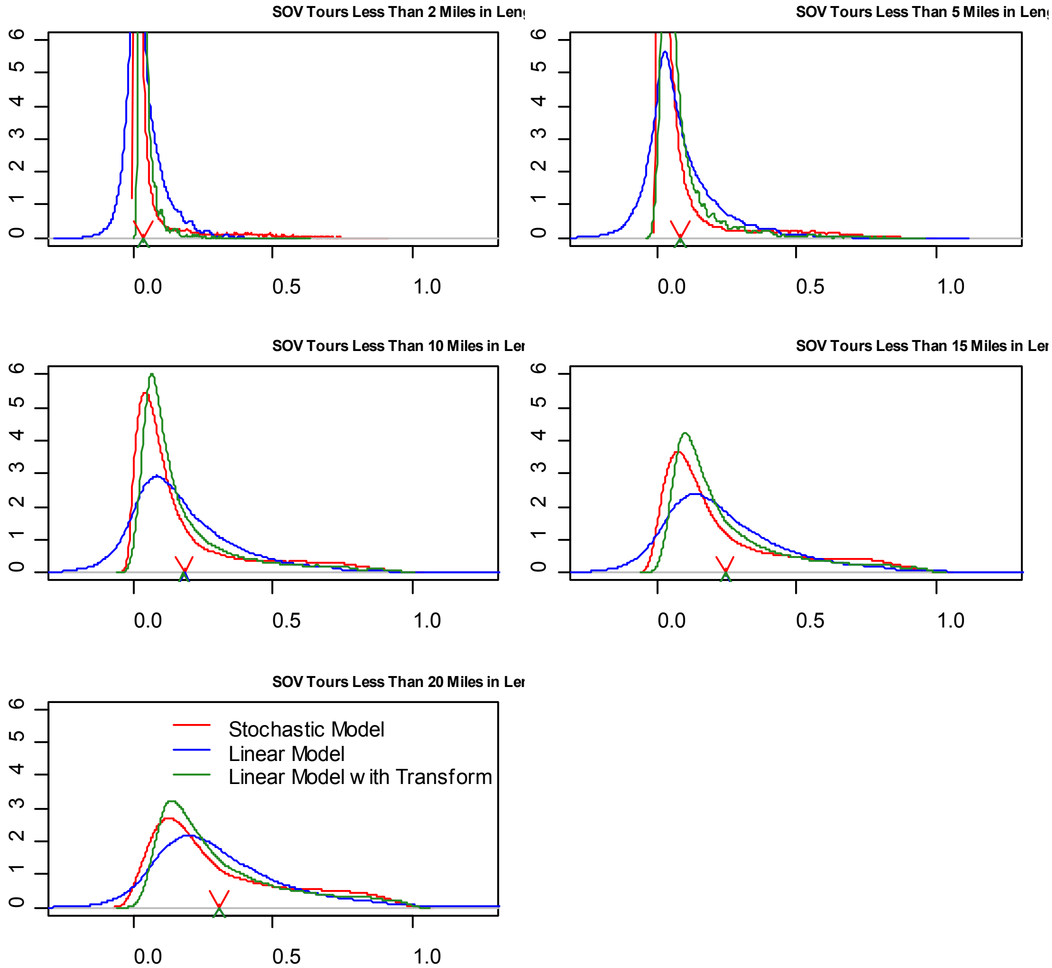


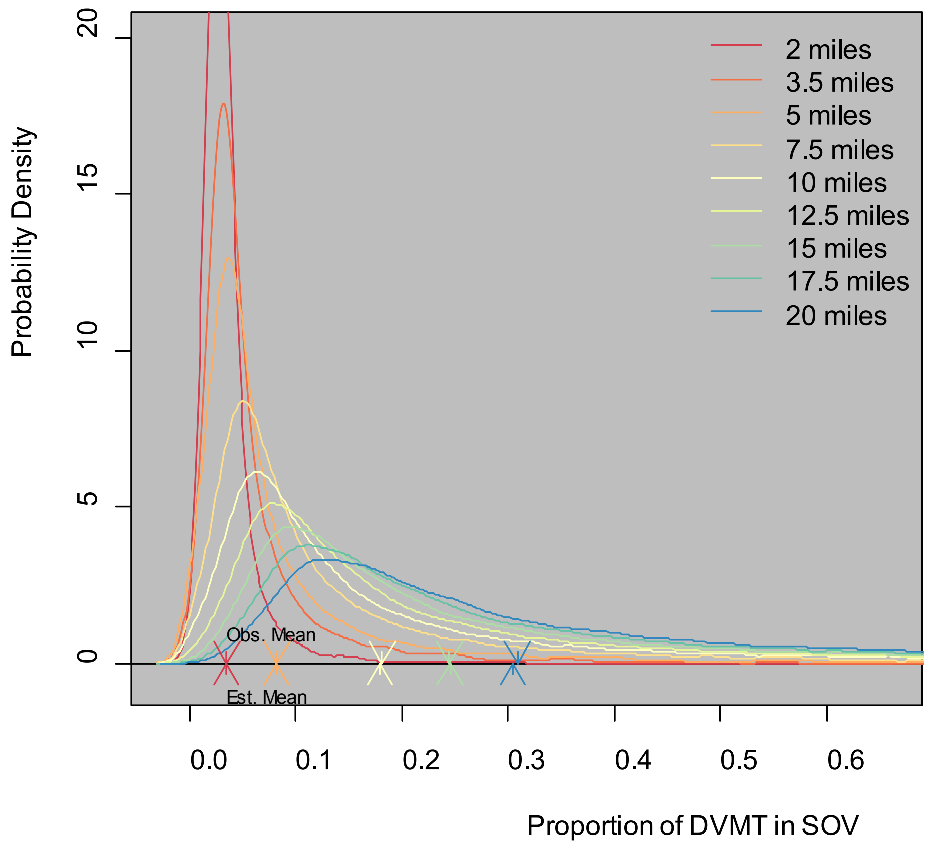
Figure 32 compares the distributions of household averages without and with the logistic transformation to the “observed averages” (i.e. calculated with the stochastic modeling approach). This shows how the linear model with the logistic transformation produces a good fit with the stochastic model results.

FIGURE 32. COMPARISON OF AVERAGE SOV PROPORTION DISTRIBUTIONS



Finally, since the objective for this model is to be able to predict the average SOV DVMT proportion for any household given any specified tour mileage threshold value between 2 miles and 20 miles, the final model needs to interpolate between the results of the different distance models. For example, the results for a 7 mile round-trip threshold would be interpolated between the model results for a 5 mile threshold and the model results for a 10 mile threshold. Figure 33 shows the distributions in household SOV mileage proportions that result from applying the models with interpolation to a range of thresholds. It also compares the mean values estimated for the 2, 5, 10, 15, and 20 mile thresholds with the mean values from the survey.

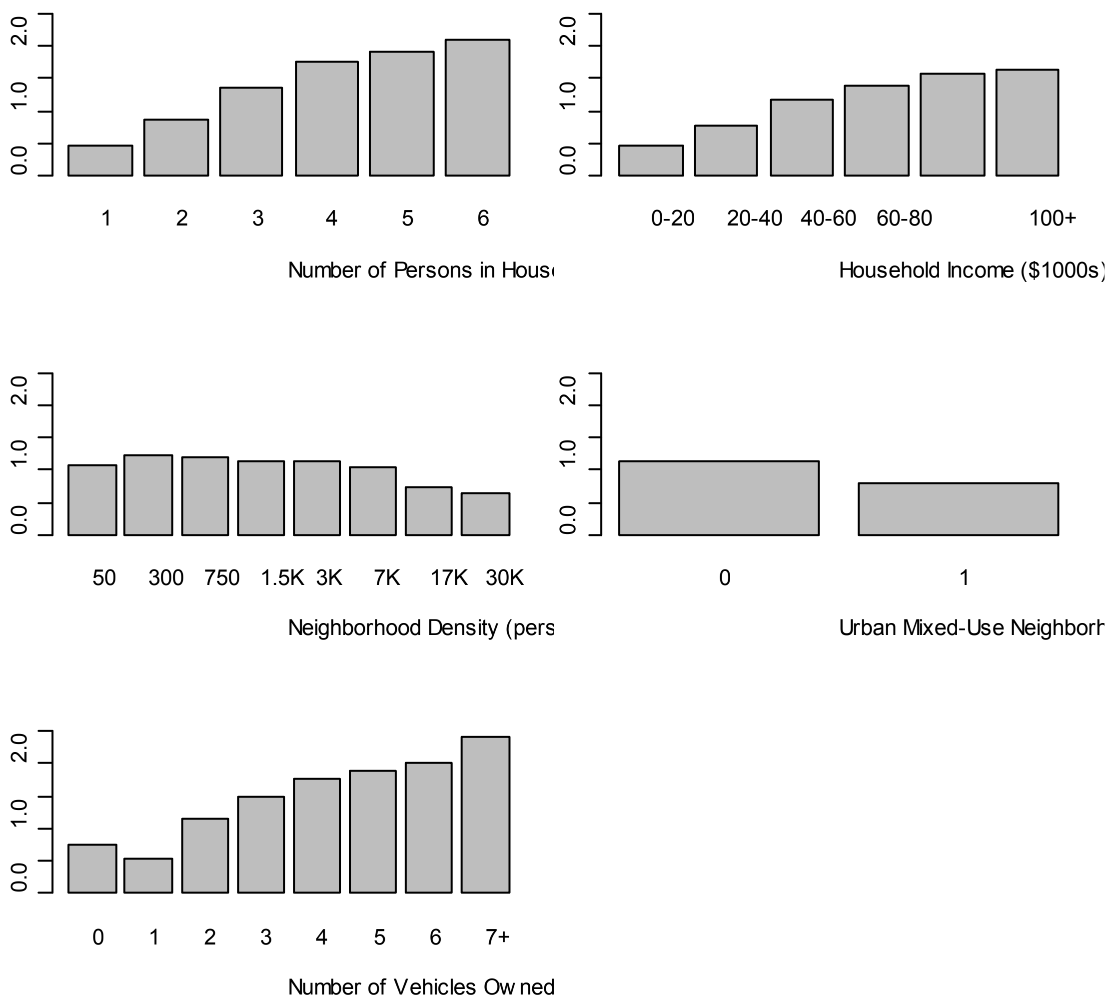
FIGURE 33. COMPARISON OF MODELED DISTRIBUTIONS OF SOV TRAVEL PROPORTIONS BY TOUR MILEAGE THRESHOLD



Estimating a Light Vehicle Ownership Model

A light vehicle ownership model was estimating using NHTS survey data on the number of full-sized bicycles in the household. Figure 34 shows how the mean number of full-sized bicycles owned varies with household and environmental characteristics.

FIGURE 34. MEAN NUMBER OF FULL-SIZED BICYCLES OWNED PER HOUSEHOLD BY HOUSEHOLD TYPE AND ENVIRONMENTAL CHARACTERISTICS



Linear models were estimated to predict the number of bicycles owned by a household based on the ages of persons in the household (AgeXtoY), the household income (Hhincttl), household size (Hhsize), vehicle ownership rate (VehPerDrvAgePop), and natural log of population density (LogDen). Table 58 shows the model estimation results for the metropolitan household model. Table 59 shows the results for the non-metropolitan household model.

The function written to implement the light vehicle ownership model allows the user to input a target light vehicle ownership rate (average ratio of light vehicles to driver age population). The function uses a binary search algorithm to adjust the intercept until the population average rate achieves the target. A target input value of NA leaves the intercept unadjusted. Figures 35 and 36 show the distributions of households by number of light vehicles owned given different target light vehicle ownership rates for metropolitan area and non-metropolitan area households respectively.

TABLE 58. METROPOLITAN HOUSEHOLD LIGHT VEHICLE OWNERSHIP MODEL

```
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)               2.395e-01  3.184e-02   7.521 5.71e-14 ***
Census_rMidwest           1.863e-01  2.699e-02   6.901 5.38e-12 ***
Census_rSouth            -1.468e-01  2.236e-02  -6.568 5.26e-11 ***
Census_rWest             -1.519e-02  2.833e-02  -0.536  0.59179
Hhsize                    1.661e-01  9.655e-03  17.198  < 2e-16 ***
Hhincttl:Age15to19        3.571e-06  4.878e-07   7.322 2.57e-13 ***
Hhincttl:Age30to54        2.488e-06  2.104e-07  11.821  < 2e-16 ***
Hhincttl:Age55to64        1.720e-06  3.764e-07   4.570 4.92e-06 ***
Age15to19:VehPerDrvAgePop  2.168e-01  3.856e-02   5.623 1.91e-08 ***
VehPerDrvAgePop:Age20to29  1.643e-01  3.565e-02   4.609 4.07e-06 ***
Age30to54:VehPerDrvAgePop  1.992e-01  1.591e-02  12.521  < 2e-16 ***
Age55to64:VehPerDrvAgePop  2.123e-01  2.775e-02   7.652 2.10e-14 ***
VehPerDrvAgePop:Age65Plus  1.484e-01  2.780e-02   5.338 9.55e-08 ***
Age20to29:LogDen         -1.404e-02  4.626e-03  -3.034  0.00242 **
Age30to54:LogDen         -1.574e-02  2.836e-03  -5.551 2.90e-08 ***
Age55to64:LogDen         -2.644e-02  4.650e-03  -5.687 1.32e-08 ***
Age65Plus:LogDen         -2.471e-02  3.634e-03  -6.801 1.08e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.131 on 15462 degrees of freedom
  (35 observations deleted due to missingness)
Multiple R-squared: 0.226, Adjusted R-squared: 0.2252
F-statistic: 282.2 on 16 and 15462 DF,  p-value: < 2.2e-16
```

TABLE 59. NON-METROPOLITAN HOUSEHOLD LIGHT VEHICLE OWNERSHIP MODEL

```
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                 1.684e-01  2.544e-02   6.619 3.69e-11 ***
Census_rMidwest             2.554e-01  1.838e-02  13.893  < 2e-16 ***
Census_rSouth              -3.935e-01  2.159e-02 -18.229  < 2e-16 ***
Census_rWest               -2.549e-01  2.495e-02 -10.216  < 2e-16 ***
Hhsize                      1.562e-01  7.000e-03  22.309  < 2e-16 ***
Hhincttl:Age15to19          3.201e-06  4.716e-07   6.786 1.18e-11 ***
Hhincttl:Age30to54          2.909e-06  1.841e-07  15.795  < 2e-16 ***
Hhincttl:Age55to64          2.125e-06  3.065e-07   6.932 4.22e-12 ***
Hhincttl:Age65Plus          1.354e-06  3.243e-07   4.177 2.96e-05 ***
Age15to19:VehPerDrvAgePop   1.604e-01  2.839e-02   5.649 1.62e-08 ***
VehPerDrvAgePop:Age20to29   8.259e-02  1.358e-02   6.082 1.20e-09 ***
Age30to54:VehPerDrvAgePop   1.430e-01  1.059e-02  13.499  < 2e-16 ***
Age55to64:VehPerDrvAgePop   1.276e-01  1.640e-02   7.781 7.41e-15 ***
Age65Plus:VehPerDrvAgePop   1.151e-01  1.705e-02   6.751 1.50e-11 ***
Age15to19:LogDen            2.744e-02  5.270e-03   5.206 1.95e-07 ***
Age30to54:LogDen            6.478e-03  2.386e-03   2.715  0.00663 **
Age55to64:LogDen           -8.207e-03  3.715e-03  -2.209  0.02717 *
Age65Plus:LogDen           -2.301e-02  3.075e-03  -7.485 7.37e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.163 on 29502 degrees of freedom
  (64 observations deleted due to missingness)
Multiple R-squared: 0.2704,      Adjusted R-squared:  0.27
F-statistic: 643.2 on 17 and 29502 DF,  p-value: < 2.2e-16
```

FIGURE 35. METROPOLITAN HOUSEHOLD LIGHT VEHICLE OWNERSHIP BY TARGET OWNERSHIP RATE

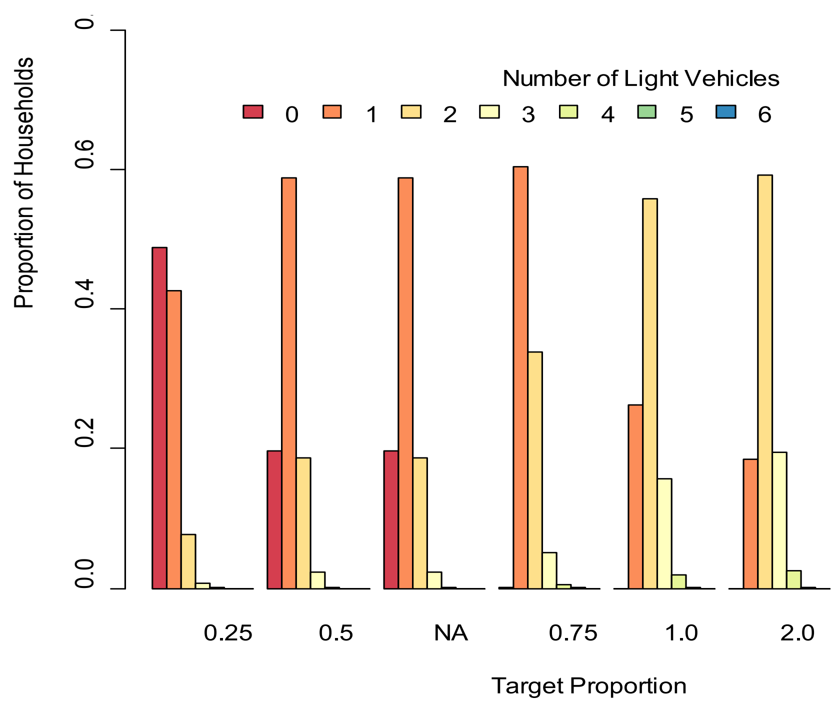
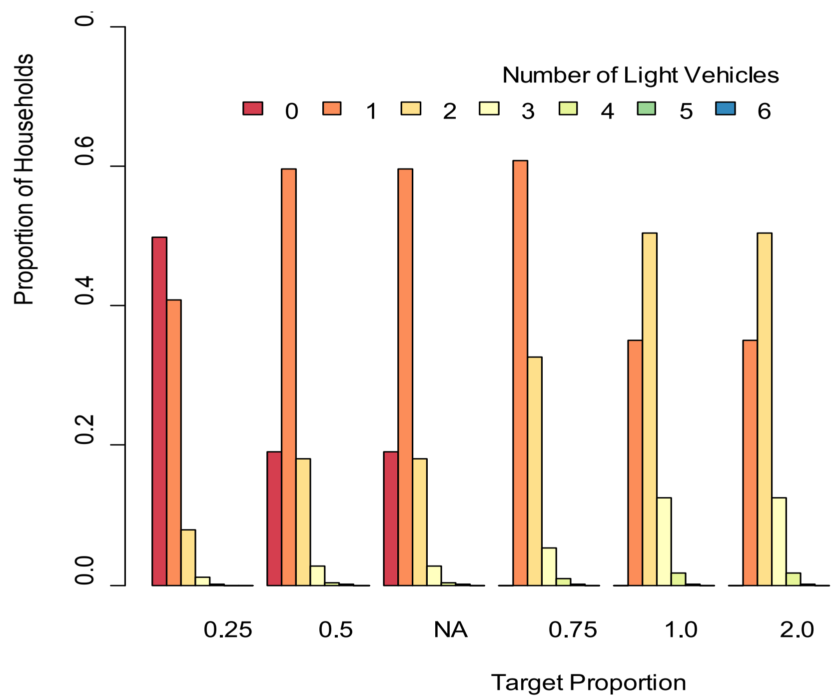


FIGURE 36. NON-METROPOLITAN HOUSEHOLD LIGHT VEHICLE OWNERSHIP BY TARGET OWNERSHIP RATE



Calculating Light Weight Vehicle DVMT

Light vehicle DVMT is calculated as follows:

LtVehDvmt = SovProp * PropSuitable * LtVehOwnRatio / SharingRatio

where:

SovProp = proportion of DVMT traveled by SOV within specified mileage threshold
(calculated by the SOV proportions model)

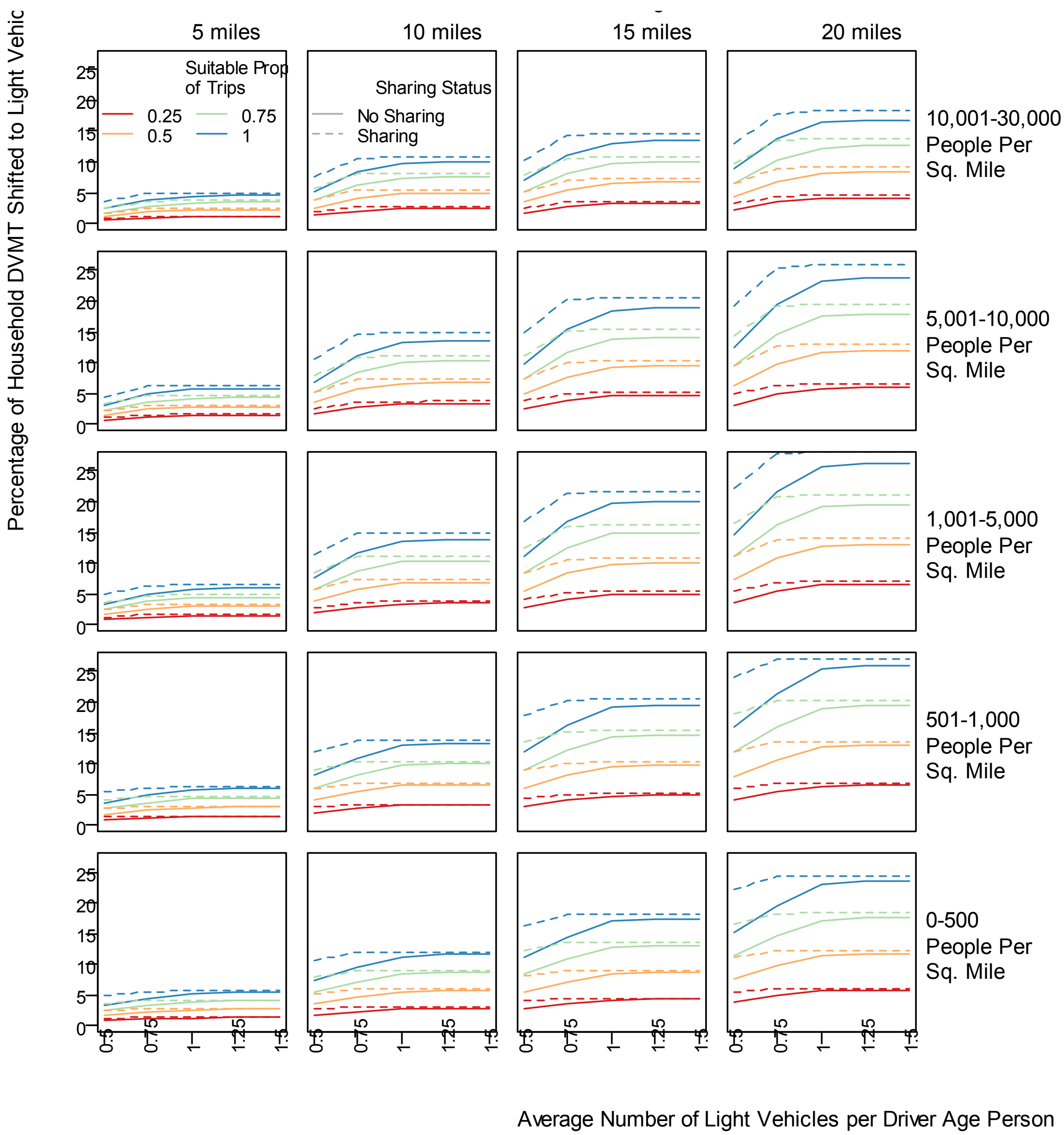
PropSuitable = proportion of SOV travel suitable for light vehicle travel
(an input assumption)

LtVehicleOwnRatio = ratio of light vehicles to number of driving age persons
(light vehicle ownership calculated by model)

SharingRatio = ratio of light vehicles to driving age persons necessary for every person to have a light vehicle available to meet their needs. (e.g. a sharing ratio of 0.5 means that one light vehicle could be shared by a 2-person household)

Figure 37 shows the results of applying the light vehicle model with different combinations of SOV tour mileage thresholds, average light vehicle ownership ratios, and light vehicle suitability proportions. The graphs are laid out such that each column corresponds to a different tour mileage threshold. Each row corresponds to a different population density. The solid lines show the results assuming no sharing of light-weight vehicles among household members. The dashed lines show the results assuming sharing among household members such that 1 light-weight vehicle can serve 2 household members.

FIGURE 37. RESPONSE OF LIGHT VEHICLE USE OF CHANGES IN INPUT VARIABLES



Testing the Light-Vehicle Model

The Metropolitan GreenSTEP estimate of base year bicycle travel for the Portland metropolitan area was compared to an estimate of bicycle travel calculated from the recent household travel survey. This was done in conjunction with the health impact assessment being completed as part of Metro's Climate Smart Communities Scenarios Project. This comparison found the GreenSTEP estimate of base year bicycle travel to be about an order of magnitude lower than the survey-based estimate of 0.28 miles per person per day. This prompted project staff from the Oregon Department of Transportation and Metro to investigate.

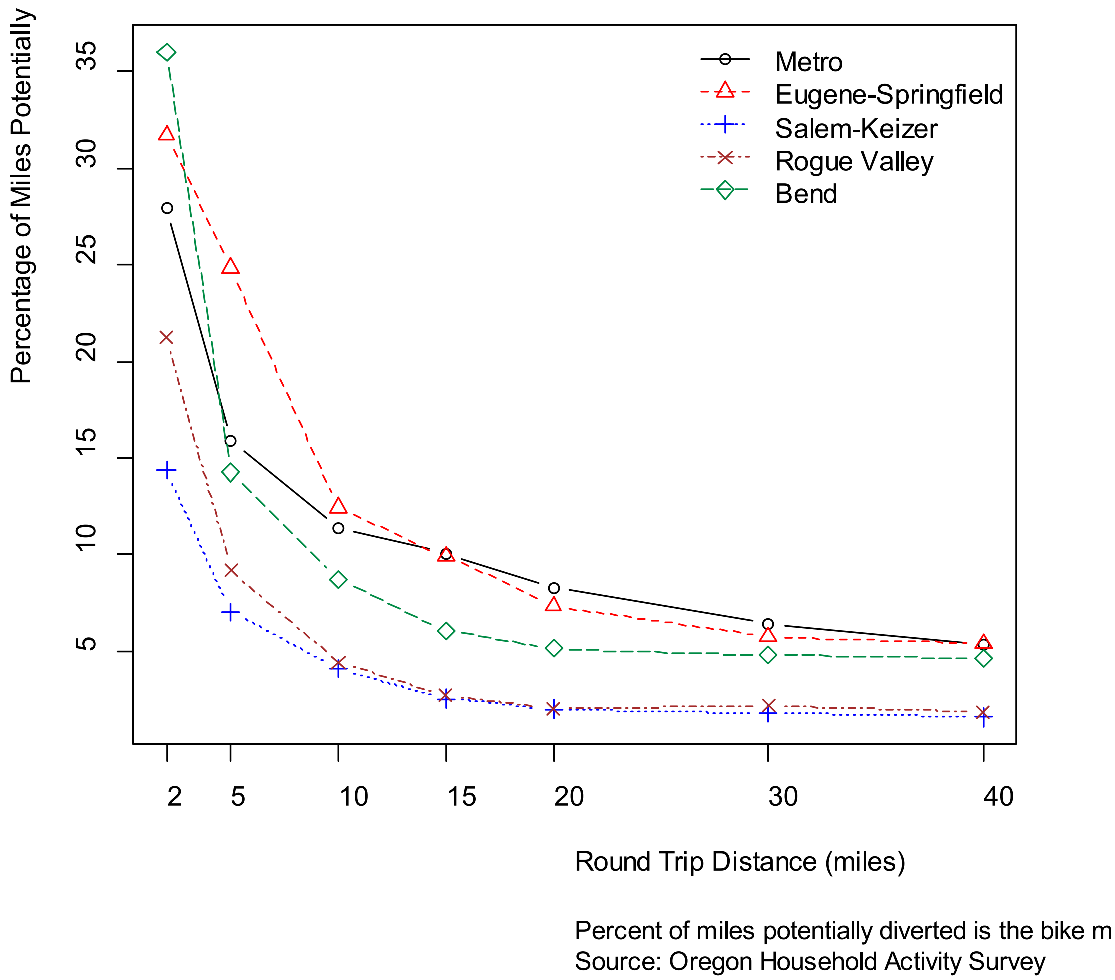
Investigation of the household survey data revealed that the assumed base year model inputs for the threshold for SOV tour lengths suitable for diversion and the percentage of SOV tours diverted were too low. The assumed SOV diversion distance threshold had been 6 miles. The diversion percentage had been 2%. Since the household survey data were not available at the time that these input assumptions were made, staff had based the assumptions on the regional transportation plan assumption that bicycle travel would be 2% of all trips 6 miles or less in length.

Examination of the recent Oregon Household Activity Survey data revealed that the 6 mile tour length was much too short. About 36% of survey bike tours were greater than that length and those tours accounted for about 71 percent of the bike tour miles. The 95th percentile bike tour mileage was almost 20 miles and the longest recorded tour was 40 miles. The total recorded bicycle mileage was 5.4% of the sum of the bicycle mileage and SOV mileage within a 40-mile tour length threshold. Figure 38 shows the percentage of diverted miles by tour length threshold for 5 of Oregon's metropolitan areas, including the Portland metropolitan area.

Metropolitan GreenSTEP was rerun with inputs of a 20 mile tour length threshold and a proportion suitable for diversion of 0.1. The 20 mile threshold is the largest threshold that GreenSTEP was designed to accommodate. The 0.1 proportion suitable was used to compensate for the tour length threshold limitation. The ratio of total bike miles to the sum of total bike miles and SOV miles within a 20-mile tour distance threshold is 10.3%.[17] When these inputs were used in GreenSTEP the resulting estimate of bicycle travel was 0.32 miles per person per day. This is within 14% of the survey-based estimate; quite close given the general nature of the GreenSTEP model.

[17] These statistics only include utilitarian bicycle travel. They do not include recreational bike riding.

FIGURE 38. PERCENTAGE OF SOV MILES POTENTIALLY DIVERTED TO BICYCLING IN TOURS WITH ROUND TRIP DISTANCES LESS THAN OR EQUAL TO SPECIFIED VALUES



Calculating Walk Trips

The GreenSTEP model and RSPM also include a walk model which estimates the daily number of walk trips for each household. This model was added in order to provide an indicator of the effect of land use and transportation policies on active transportation. The model does not affect the amount of household DVMT because land use and transportation policies directly affect the calculations of DVMT.

The walk model includes two components, a binomial logit model which determines the probability that a walk trip is taken and a linear model which estimates the number of walk trips if a walk trip is taken. The average number of walk trips is the product of these values. Tables 60 and 61 show the model estimation results for the two models. The model variables are as follows:

- Age0to14 – number of persons in the household with ages less than or equal 14
- Age15to19 – number of persons between the ages of 15 and 19

- Age20to29 – number of persons between the ages of 20 and 29
- Age65Plus – number of persons 65 or older
- Htppopdn – population density of the neighborhood (persons per square mile)
- Urban – whether the household lives in an urban mixed use neighborhood
- Hhincttl – total annual household income in 2001 dollars
- Hhsize – number of persons in the household
- VehPerDrvAgePop – ratio of vehicles to drivers in the household

TABLE 60. WALK TRIP PROBABILITY MODEL

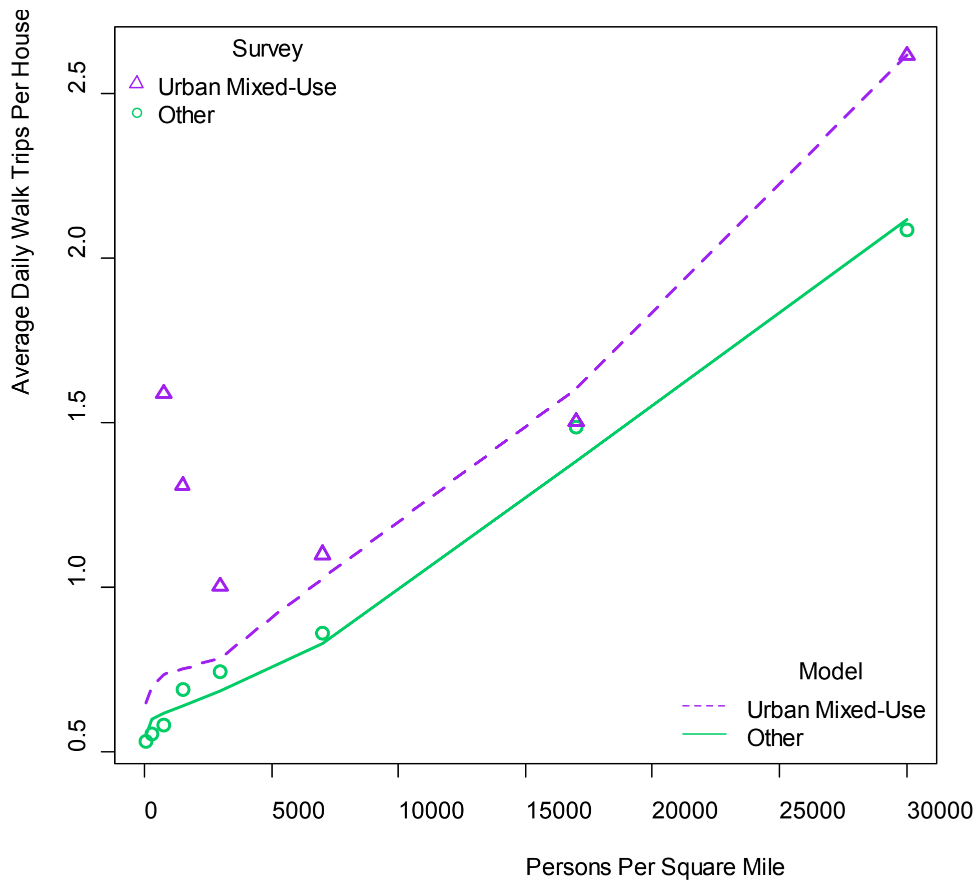
```
                            Estimate Std. Error z value Pr(>|z|)
(Intercept)               -1.211e+00  3.829e-02 -31.621  < 2e-16 ***
Age0to14                   1.308e-01  2.623e-02   4.989 6.06e-07 ***
VehPerDrvAgePop           -4.632e-01  2.935e-02 -15.778  < 2e-16 ***
Age20to29                  2.810e-01  4.791e-02   5.865 4.49e-09 ***
Age65Plus                 -1.980e-01  3.784e-02  -5.232 1.67e-07 ***
Htppopdn                   4.231e-05  2.153e-06  19.655  < 2e-16 ***
Urban                      2.052e-01  4.201e-02   4.884 1.04e-06 ***
Hhincttl                   5.831e-06  3.094e-07  18.844  < 2e-16 ***
Age0to14:VehPerDrvAgePop   6.772e-02  2.321e-02   2.917  0.00353 **
VehPerDrvAgePop:Age20to29 -2.880e-01  4.850e-02  -5.938 2.89e-09 ***
VehPerDrvAgePop:Age65Plus  8.682e-02  3.769e-02   2.303  0.02126 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 61534  on 54785  degrees of freedom
Residual deviance: 58726  on 54775  degrees of freedom
  (110 observations deleted due to missingness)
AIC: 58748

Number of Fisher Scoring iterations: 4
```

TABLE 61. MODEL OF NUMBER OF WALK TRIPS

```
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                1.702e+00  7.511e-02  22.659  < 2e-16 ***
Hhsize                     5.733e-01  1.671e-02  34.315  < 2e-16 ***
Age65Plus                 -1.732e-01  3.464e-02  -5.001 5.76e-07 ***
VehPerDrvAgePop           -2.683e-01  4.239e-02  -6.330 2.53e-10 ***
Htppopdn                   5.293e-05  3.956e-06  13.381  < 2e-16 ***
Urban                      1.676e-01  8.110e-02   2.067  0.03880 *
Hhincttl                  -1.916e-06  6.366e-07  -3.009  0.00263 **
Age15to19:VehPerDrvAgePop -4.245e-01  4.234e-02 -10.026  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.443 on 13651 degrees of freedom
Multiple R-squared: 0.1224,      Adjusted R-squared: 0.1219
F-statistic: 271.9 on 7 and 13651 DF,  p-value: < 2.2e-16
```

Figure 39 shows walk trip rates by census tract population density for households in mixed-use urban settings and in other settings. Averages calculated from the NHTS household survey data are plotted as points. Model results are shown by the plotted lines. Except for the urban mixed-use household results at low densities, the model predictions match the survey estimates reasonably well. The survey estimates for the lower density urban mixed-use households appear to be anomalous.

FIGURE 39. ESTIMATED AVERAGE DAILY WALK TRIPS PER HOUSEHOLD. COMPARISON OF SURVEY-BASED ESTIMATES AND WALK MODEL ESTIMATES AS A FUNCTION OF POPULATION DENSITY AND NEIGHBORHOOD TYPE



Calculate vehicle types and ages and assign DVMT to Vehicles

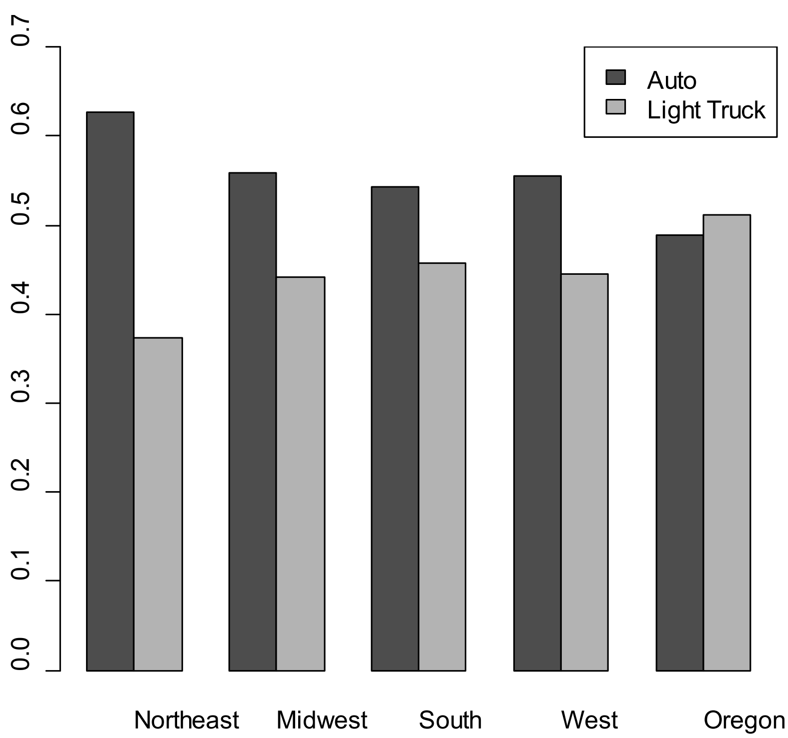
The vehicle fleet models were estimated using records from the NHTS and a 2009 inventory of Oregon vehicles from the Oregon DMV. The western Census region subset of the NHTS data was used for building the light truck and vehicle age models because light truck percentages and distribution of vehicle ages is significantly different in the west than in other regions of the country.

Modeling Vehicle Type

Figure 40 shows that the west tends to have higher light truck (pickups, vans, sport utility vehicles) ownership than average and that light truck ownership in Oregon exceeds auto ownership.

A light truck model was developed to determine which household vehicles, if any, would be light trucks. The model was built using the NHTS data for the western Census region to have the model most closely match Oregon conditions. In order to match Oregon light truck proportions, the model was built to be self-calibrating so that it can match a specified truck proportion.

FIGURE 40. AUTO AND LIGHT TRUCK PROPORTIONS BY REGION



A binary logit model is used to predict vehicle type for each household vehicle. Table 62 shows the variable coefficients and statistics for the chosen model. Variable names have the same meanings as previously described with the following additional variables:

- Hhvehcnt – number of vehicles in the household
- LogDen – natural log of the census tract population density

The model includes both a population density and logged population density term. Plots of the relationship between population density and light truck ownership showed there to be a nonlinear relationship. The relationship with population density is approximately linear at higher densities while the relationship with the log of population density is approximately linear at lower population densities.

The same model is used for metropolitan and non-metropolitan households because the only metropolitan area characteristic in the model is the urban mixed-use development type. The value of this variable for non-metropolitan areas is zero.

This model does not include an intercept. The intercept was found not to be statistically significant, even at the 10 per cent level.

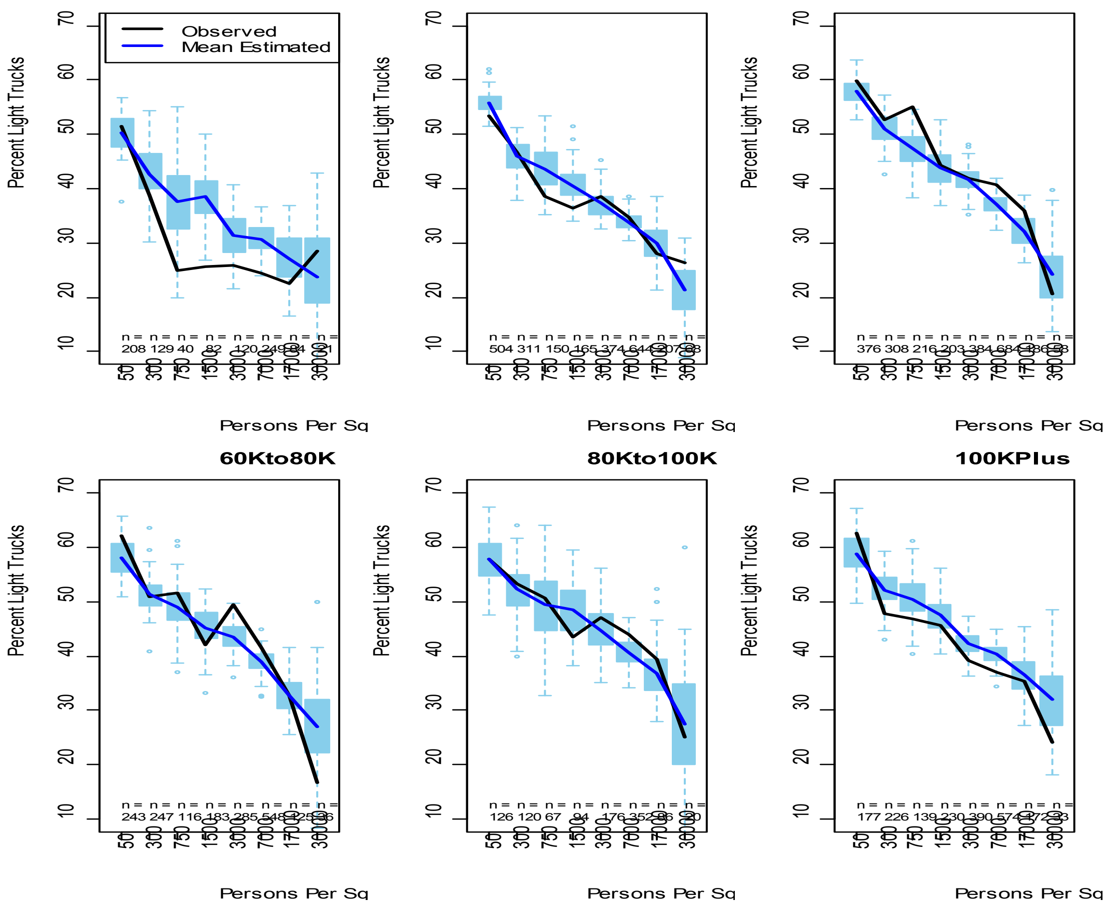
TABLE 62. LIGHT TRUCK TYPE MODEL

```
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)       -7.866e-01  1.534e-01  -5.128 2.93e-07 ***
Hhincttl           5.010e-06  1.774e-06   2.824 0.004745 **
LogDen            -1.517e-01  1.165e-02 -13.027  < 2e-16 ***
Urban             -1.934e-01  6.423e-02  -3.012 0.002599 **
Hhvehcnt           6.009e-01  6.021e-02   9.980  < 2e-16 ***
Hhsize             2.873e-01  3.913e-02   7.343 2.09e-13 ***
Hhincttl:Hhsize    1.744e-06  4.840e-07   3.602 0.000315 ***
Hhincttl:Hhvehcnt -3.793e-06  6.449e-07  -5.881 4.07e-09 ***
Hhvehcnt:Hhsize   -8.627e-02  1.161e-02  -7.432 1.07e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 14994  on 10975  degrees of freedom
Residual deviance: 14354  on 10967  degrees of freedom

AIC: 14372

Number of Fisher Scoring iterations: 4
```

Although the light truck model will predict the likelihood that a vehicle is a light truck, it is also important to be able to match current and past Oregon light truck proportions and to evaluate the effects of different fleet proportions in the future. Light truck proportion targets are applied at the county level to reflect localized differences. Targets are matched by adding a constant to the model. The appropriate sign and size of the constant necessary to match a target light truck proportion is automatically calculated by the function that implements the light truck model using a binary search algorithm.

Figure 41 shows how well the light truck model reproduces the relationship of light truck ownership to household income and population density in the survey. The blue box and whiskers plots show the range of model results over 100 model runs as applied to the western Census region household data. The dark blue lines show mean values by density. The black lines show the survey average values.

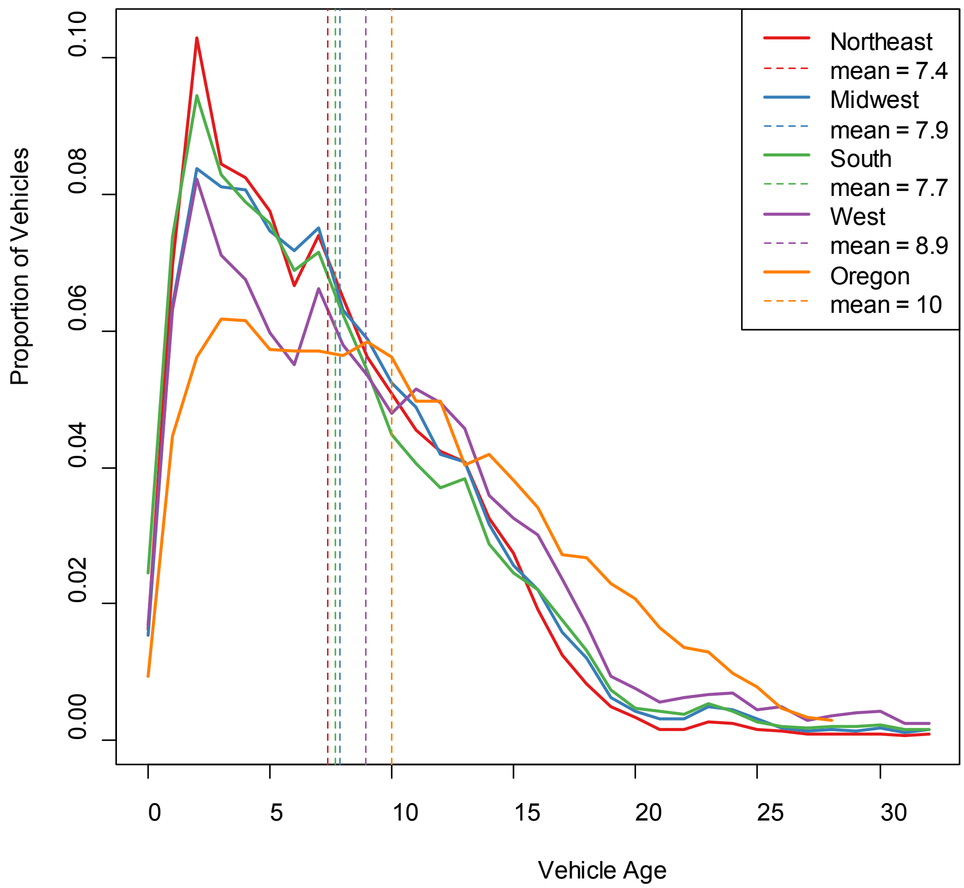
FIGURE 41. ESTIMATED AND OBSERVED LIGHT TRUCK OWNERSHIP BY INCOME GROUP AND DENSITY (100 MODEL RUNS)



Modeling Vehicle Age

Figure 42 shows vehicle age distributions by Census region and for Oregon. The mean age for vehicles owned by western region households is about a year or more older than the mean values for households located in other parts of the country and is even older in Oregon.

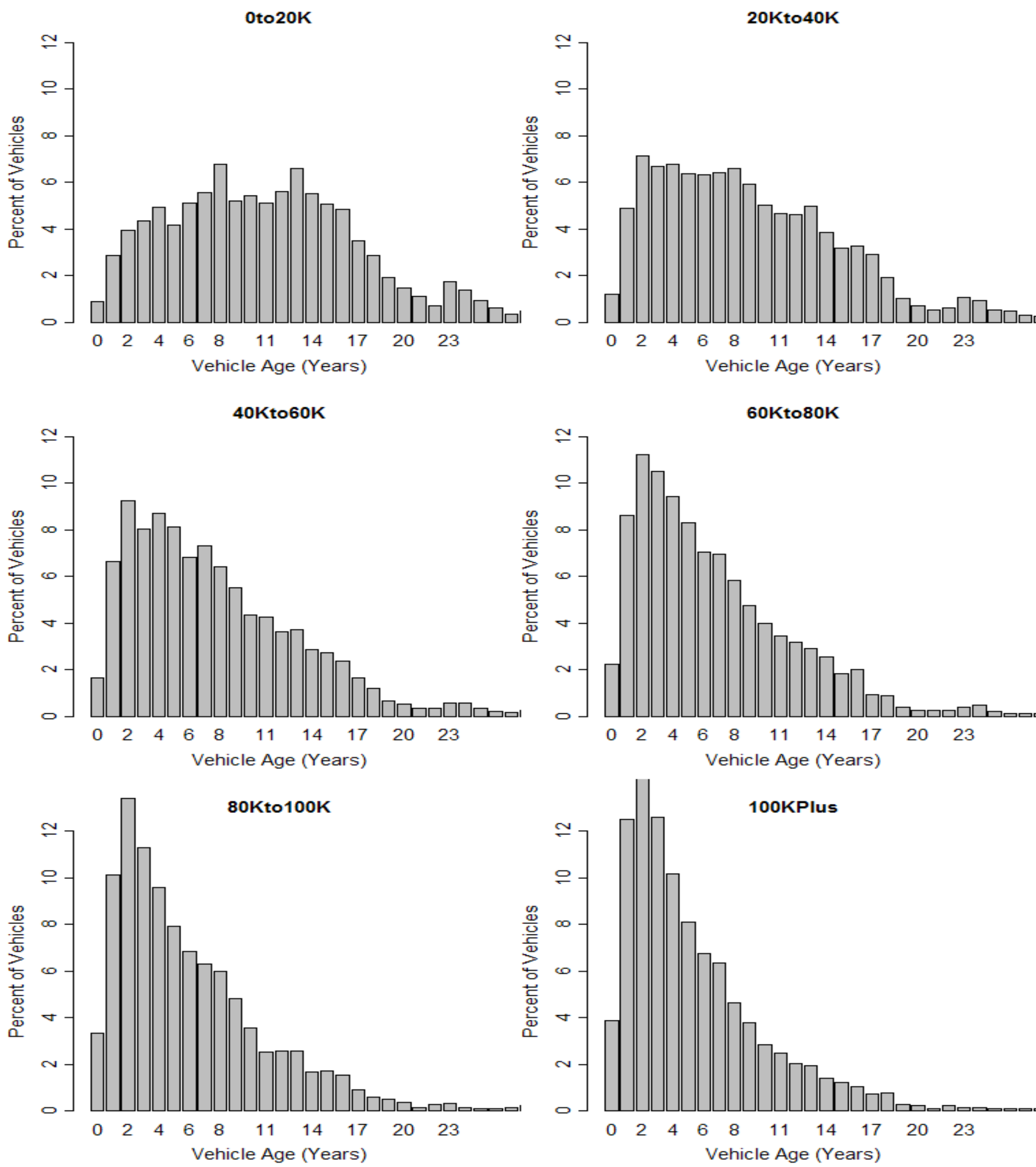
FIGURE 42. VEHICLE AGE DISTRIBUTION BY REGION



It is important that the model be responsive to the relationship between household income and vehicle age. Wealthier households tend to own newer vehicles as shown in Figure 43. This responsiveness is important because vehicle age affects fuel economy, which affects fuel expenditures.

The Oregon DMV data does not include information about household income. Therefore, the western Census region subset of the NHTS data was used to estimate this model. The estimated model was then calibrated to match the Oregon vehicle age distribution.

FIGURE 43. VEHICLE AGE DISTRIBUTION BY HOUSEHOLD INCOME GROUP WESTERN CENSUS REGION HOUSEHOLDS

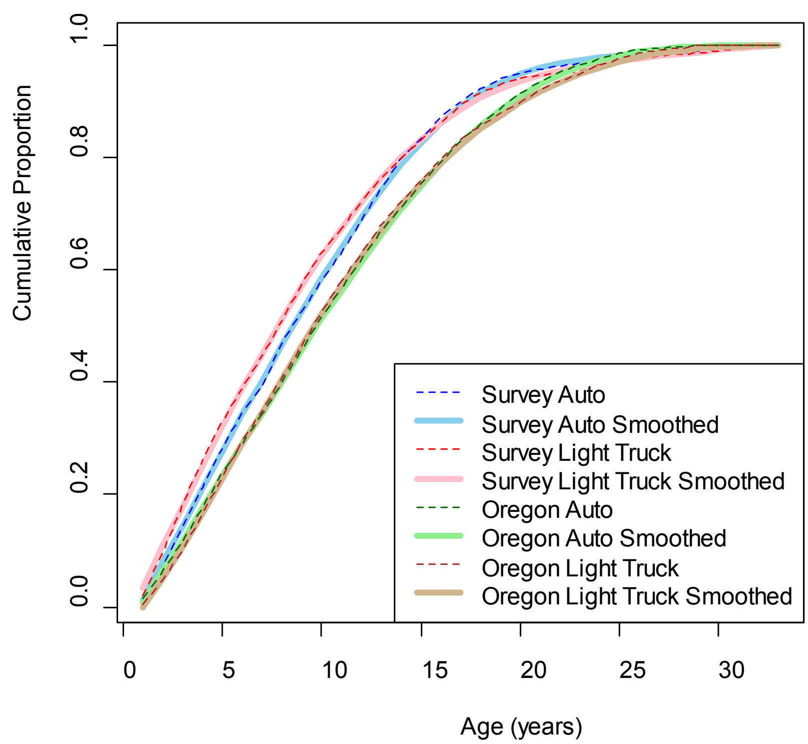


The NHTS western Census region survey data was used to calculate the joint and marginal distributions of vehicles by age and household income. This was done separately for automobiles and light trucks. These joint distributions are used as sampling distributions in a Monte Carlo process to assign ages to household vehicles. An iterative proportional fitting (IPF) procedure is used to adjust the joint distribution to respond to changes in the income and vehicle age marginal distributions.

Changes in the income margin do not need to be modeled. They are an outcome of the application of the vehicle ownership and light truck models. It is only necessary to tabulate the number of autos (or light trucks) by income group and calculate proportions.

The GreenSTEP and RSPM models use a simple approach to model the vehicle age margin. The distribution of vehicle ages is modeled by specifying an assumed or desired change in the 95th percentile age of the fleet and adjusting the cumulative distribution accordingly. The adjusted cumulative distribution is then converted into a regular distribution that is the new age margin. Figure 44 shows the cumulative distributions for automobiles and light trucks in the NHTS survey data and Oregon vehicle data. The distributions used in the model are smoothed, but not much smoothing is necessary.

FIGURE 44. CUMULATIVE PROPORTIONS OF VEHICLES OF SPECIFIED AGE OR YOUNGER



Several steps were taken to build the auto (light truck) table of joint probability by age and household income. First, a joint table was constructed using the NHTS survey data for the western Census region. The income margin was calculated as a simple tabulation of the data. The age margin was constructed by converting the smoothed cumulative age distribution for the NHTS western region data into a regular age distribution. Then an IPF procedure was used to simultaneously balance the matrix and smooth the distributions for each income group. Figure 45 shows the smoothed auto age distributions for automobiles and Figure 46 shows the corresponding distributions for light trucks.

FIGURE 45. SMOOTHED DISTRIBUTION OF AUTO VEHICLE AGES BY INCOME GROUP

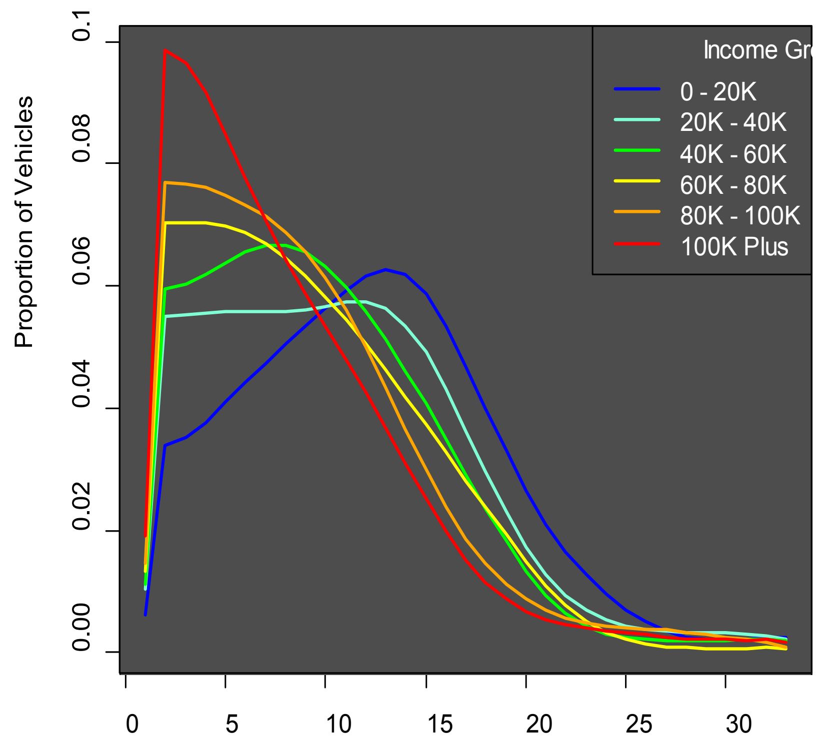
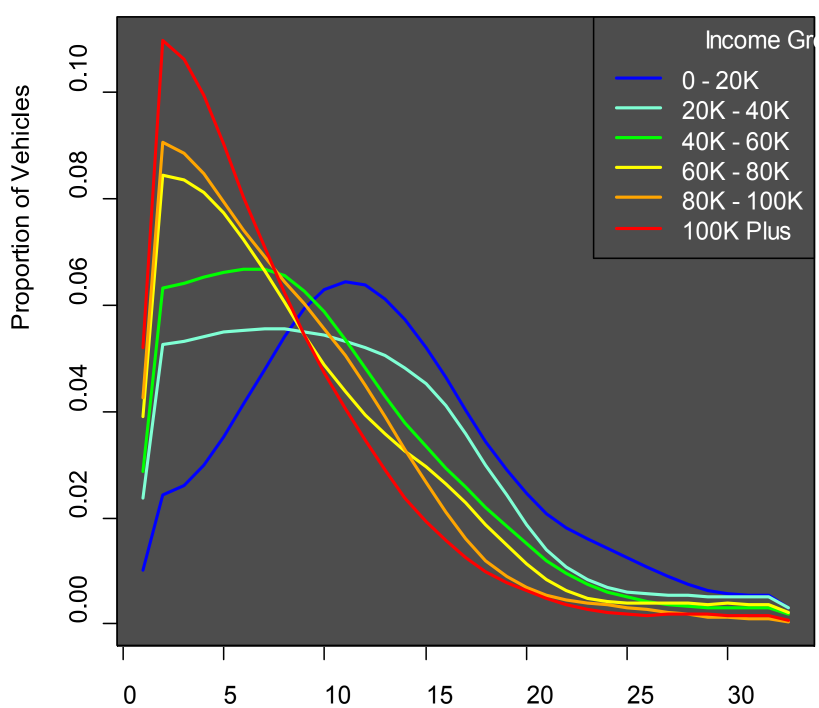


FIGURE 46. SMOOTHED DISTRIBUTION OF LIGHT TRUCK VEHICLE AGES BY INCOME GROUP



Since a Monte Carlo process is used to determine vehicle ages, each run of the model will produce different results that will be noticeable for small populations. Figure 47 shows the results of running the auto vehicle age model 20 times on the NHTS western region survey households. It can be seen that all of the model runs together describe a band of probable results consistent with the survey values. Figure 48 shows the results for light trucks.

FIGURE 47. OBSERVED AND ESTIMATED AUTO AGE PROPORTIONS BY INCOME GROUP (20 MODEL RUNS)

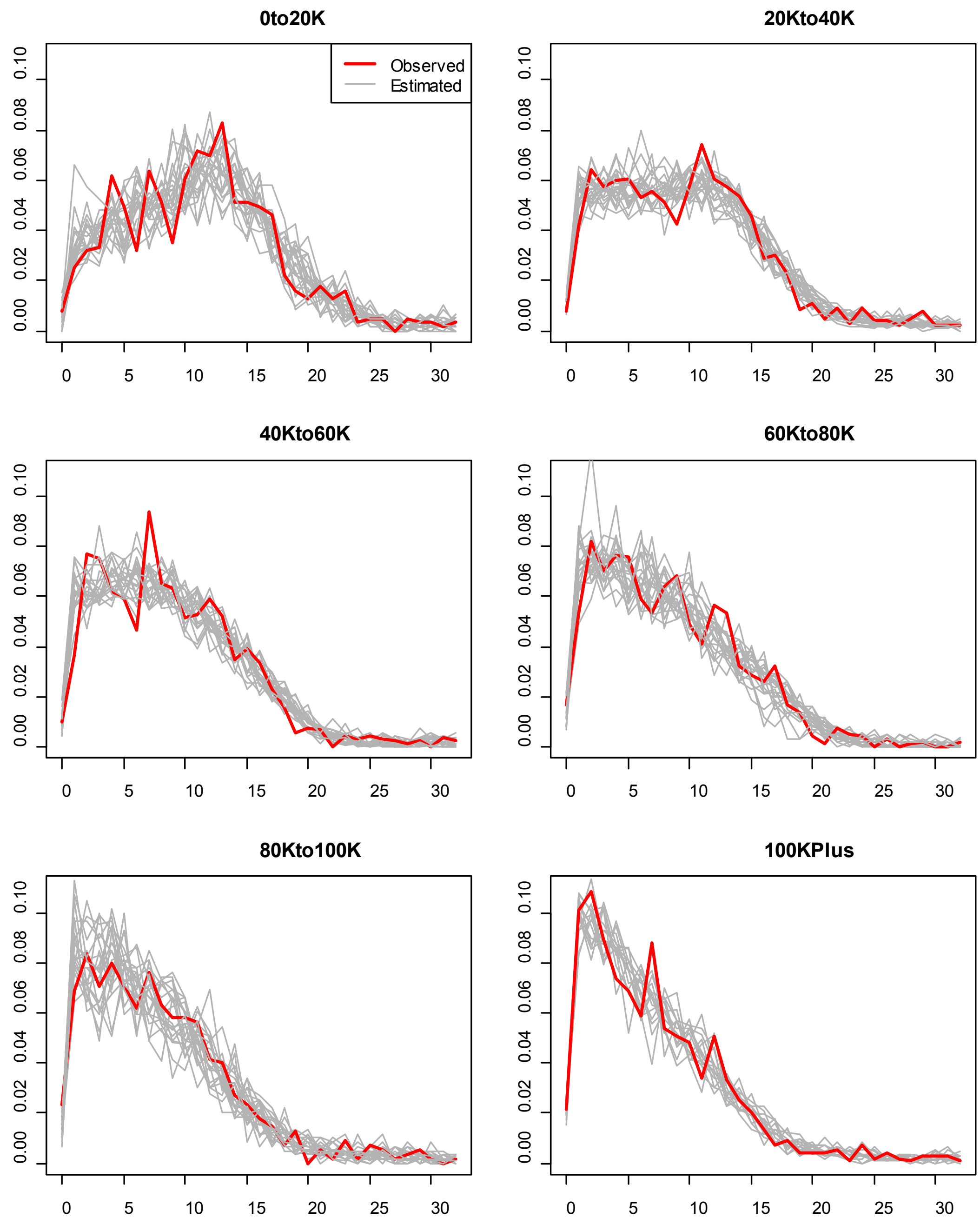
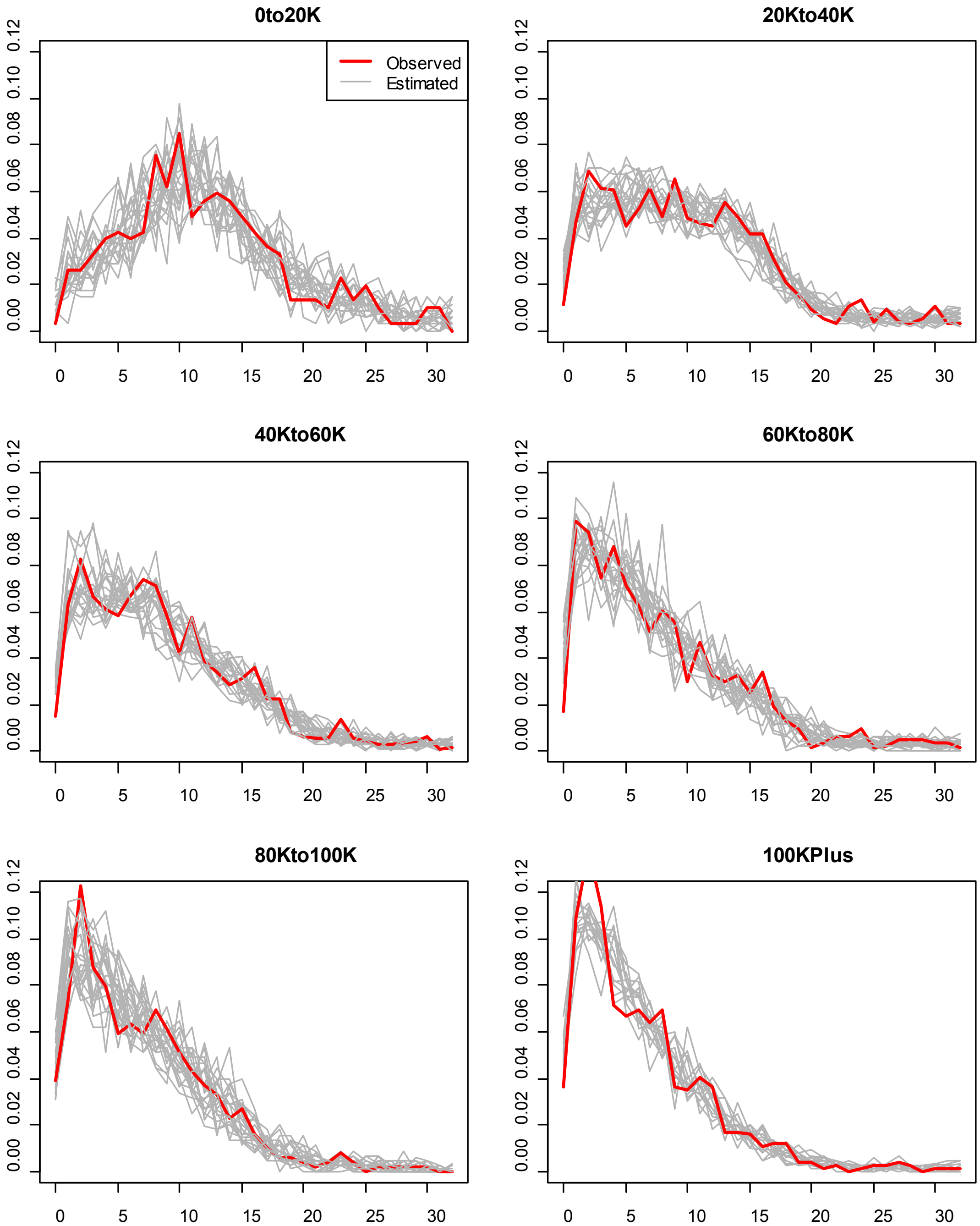
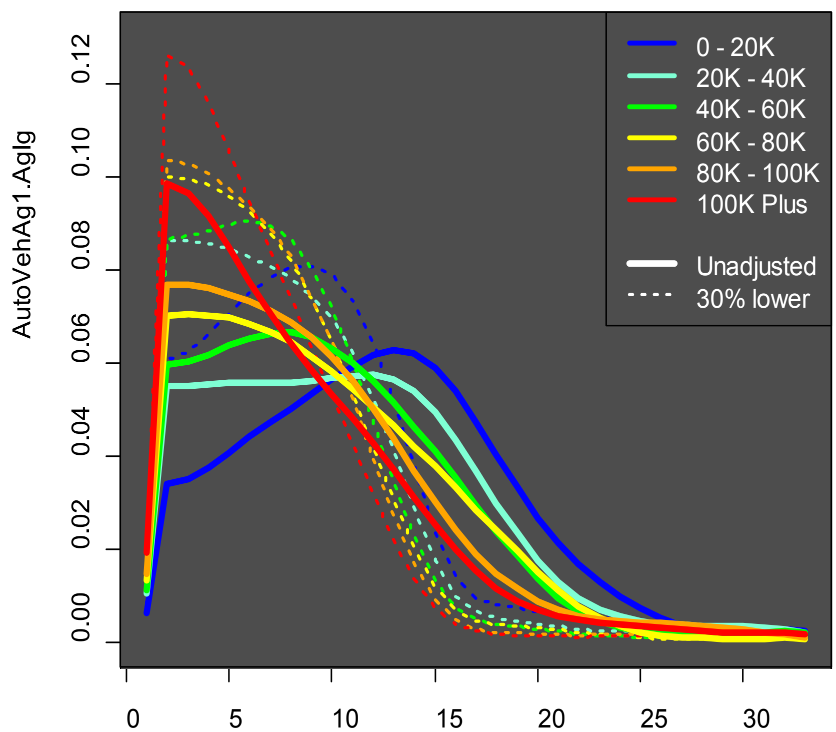


FIGURE 48. OBSERVED AND ESTIMATED LIGHT TRUCK AGE PROPORTIONS BY INCOME GROUP (20 MODEL RUNS)



This approach to modeling vehicle fleet ages allows future scenarios to be specified easily. The 95th percentile age is used as a pivot point for adjusting the fleet age distribution. For example, if the model user inputs a value of 0.8, the 95th percentile age is adjusted to be 80 per cent of the reference age distribution. Ages on either side of the new 95th percentile age are then adjusted proportionately. Figure 49 shows the effect of reducing the 95th percentile age of automobiles by 30 per cent.

FIGURE 49. AUTO AGE PROPORTIONS BY INCOME GROUP WITH/WITHOUT REDUCING THE 95TH PERCENTILE AGE



The joint distribution was calibrated to match the Oregon fleet age distribution by iterative proportional fitting. The estimated age margin was replaced by a distribution constructed by converting the smoothed cumulative age distribution for the Oregon vehicle data. The matrix was rebalanced to create a joint distribution that reflects the age characteristics of the Oregon vehicle fleet. Figure 50 compares the smoothed auto age distributions by income group calculated from the survey data with the adjusted distributions for Oregon. Figure 51 makes a similar comparison for light trucks.

FIGURE 50. ESTIMATED AND CALIBRATED AUTO AGE PROPORTIONS BY INCOME GROUP

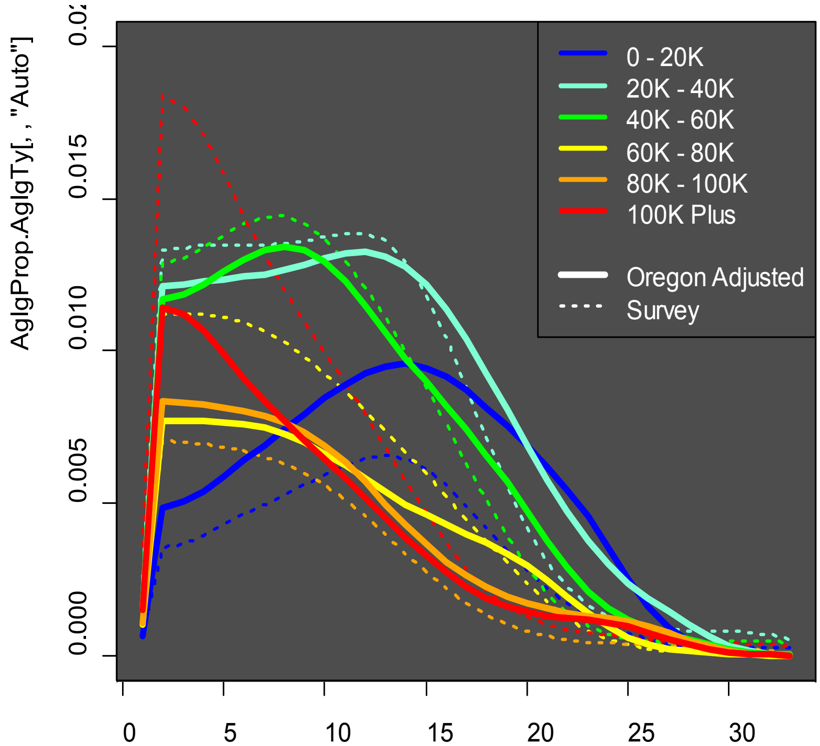
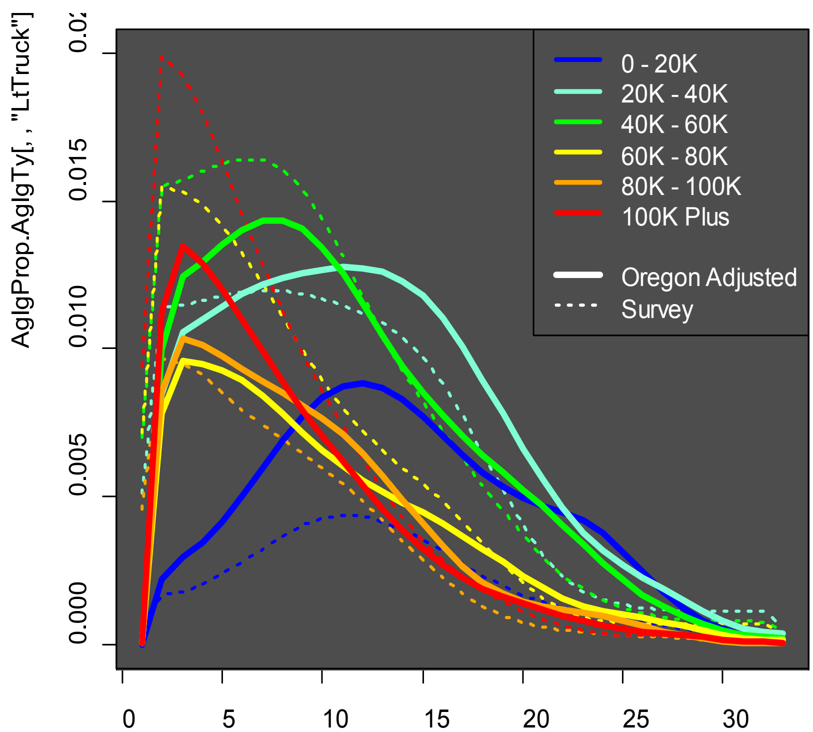


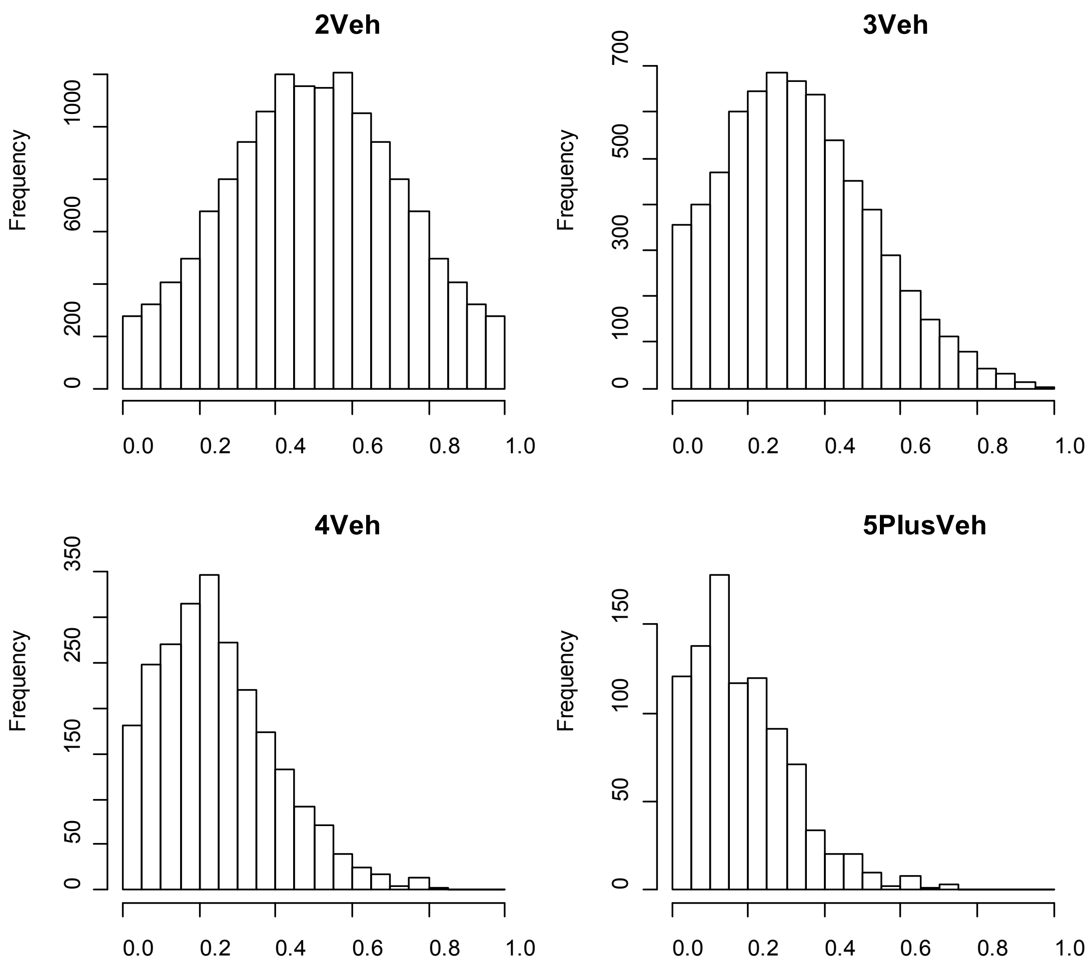
FIGURE 51. ESTIMATED AND CALIBRATED LIGHT TRUCK AGE PROPORTIONS BY INCOME GROUP



Assigning DVMT to Household Vehicles

Household DVMT is allocated among the vehicles in the household by a Monte Carlo process which uses sampling distributions derived from data on annual miles traveled by vehicle in the survey data (Figure 52). The results are randomized so that there is no sampling order bias.

FIGURE 52. DISTRIBUTION OF VEHICLE MILEAGE PROPORTIONS BY NUMBER OF HOUSEHOLD VEHICLES



The random assignment of mileage proportions to vehicles assumes that households do not optimize the use of their vehicles to minimize fuel use. This is the default case for running the model. However, the user can input a value of the proportion of households assumed to be optimizers. This is explained in the next section.

The 95th percentile and maximum household DVMT values are apportioned to vehicles in the same proportions as the average household DVMT.

Assign Vehicle Powertrains, MPG and MPkWh, and Optimize Travel between Vehicles

The GreenSTEP and RSPM models recognizes four vehicle powertrains:

1. Internal Combustion Engines (ICE): These are standard gasoline or diesel powered vehicles that have no electrical power assistance other than perhaps stop-start technology.
2. Hybrid Electric Vehicles (HEV): These are vehicles powered by the combination of an internal combustion engine and an electric motor. Although HEVs have a battery to run the electric motor, the battery is charged through operation of the vehicle (e.g. through recovery of energy from braking). The vehicle battery is not designed be charged from an external power source.
3. Plug-in Hybrid Electric Vehicles (PHEV): These are like HEVs but they have larger batteries and electric motors so that they can be charged from an external power source and can run entirely on electricity until the battery charge is depleted. However, unlike EVs, they also have an internal combustion engine so that their range is not limited to the capacity of their battery.
4. Electric Vehicles (EV): These vehicles run solely on electricity stored on board in batteries. They must be recharged from an external power source.

Fuel cell vehicles (FCV) are not included in the model. There are a couple of reasons for this. First, fuel cell vehicles are much more costly than electric vehicles and all indications are that EV costs will decline more rapidly than FCV costs. Second, FCVs are functionally electric vehicles in which the power is stored in a different manner. In EVs, power is stored in batteries. In FCVs, power is stored in compressed hydrogen that is converted to electricity in a fuel cell. So FCVs could be modeled as EVs with longer-range batteries.

Vehicle powertrains are assigned to household vehicles based on model scenario inputs regarding powertrain proportions by vehicle model year. There is no household behavioral component to the powertrain assignment with the exception that EV assignment is limited to households whose 95th percentile DVMT is less than or equal to the mileage range of the model year EV. This is described in more detail below.

The cost of different vehicle powertrains is not an explicit consideration in assigning powertrains to household vehicles. This is part of the model design because of the large amount of uncertainty regarding future vehicle prices and the long planning time horizons. Current prices of non-ICE vehicles are not reflective of future prices because economies of scale in technological development and production are only just starting be achieved for HEVs. It will take a number of years before that happens with PHEVs and EVs. Aside from the cost of low-volume production, the major cost component for EVs and PHEVs is the cost of their batteries. Other components of these vehicles are simpler than internal combustion engines and are likely to be less expensive over the long run. The cost of batteries is anticipated to decline considerably in the coming decade. McKinsey & Company have forecasted automotive lithium ion battery packs to fall in price from $500 - $600 per kWh to about $200 per kWh in 2020 and $160 per kWh in 2025. [18]

Although vehicle costs related to powertrains are not explicitly modeled, there is implicit consideration of the relationship to household income given that EVs and other advanced vehicle technologies will be more highly represented in newer model year vehicles and higher income persons are more likely to own newer model year vehicles.

Vehicles are split into powertrain types and assigns fuel and power efficiency characteristics in several steps. Initially, all vehicles are assumed to have ICE powertrains and are assigned a fuel economy based on model inputs for average fuel economy by model year and vehicle type (i.e. auto, light truck). Fuel economy by vehicle type and model year is an input to the model. All fuel economy values are expressed in gasoline-equivalent gallons. In other words, the fuel economy values represent the mileage that can be driven on the energy contained in a gallon of gasoline.

Next, HEV and a combined category of PHEV/EV vehicles are identified. The proportions of vehicles by powertrain type for each vehicle type and model year are inputs to the model. Vehicles identified as HEV are assigned the HEV fuel economy value for their type and model year. These are inputs to the model. Vehicles that are assigned in the combined PHEV/EV category are initially assigned as PHEV and attributed with the PHEV fuel economy value for vehicle operation in charge sustaining mode[19] for the model year and vehicle type. The EV vehicles are split out from the joint category in a later step.

The split of household DVMT among household vehicles is optimized for households identified as vehicle use optimizers. These are households which split their travel among their vehicles to minimize fuel consumption. The proportion of households that are optimizers is a model input. A Monte Carlo process is used to identify optimizing households based on the input assumption on the proportion of households that optimize. The optimizing process does not change the proportional split of mileage among vehicles, it only changes which vehicles are assigned which proportions. For optimizing households, VMT proportions are ordered in the order of vehicle fuel economy. For example, if a household owns 3 cars for which the average DVMT splits are 50%, 30%, and 20%, and if the 3 vehicles have fuel economy ratings of 15 MPG, 21 MPG and 32 MPG, and if the household is an optimizer, the household will put 50% of their DVMT on the 32 MPG vehicle, 30% of their DVMT on the 21 MPG vehicle and the remaining 20% of their DVMT on the 15 MPG vehicle. If the household is not an optimizer, the vehicle use proportions are randomly assigned to the household vehicles. In order to optimize PHEV/EV combined category vehicles in this framework, an equivalent MPG must be calculated for these vehicles to account for the electricity usage. The PHEV/EV fuel economy equivalent is calculated as follows:

$$MPGe = MPG \times (1 - Eprop) + MPkWh \times 33.7 \times Eprop$$

---

[18] Russell Hensley, John Newman, and Matt Rogers, Battery technology charges ahead, McKinsey Quarterly, July 2012, https://www.mckinseyquarterly.com/Battery_technology_charges_ahead_2997

[19] Charge sustaining mode is the mode of operation when the PHEV is not being powered from energy stored in its battery pack. Vehicle power comes solely from the on-board internal combustion engine.

where:
MPGe is the fuel economy equivalent for the PHEV model year and vehicle type
MPG is the fuel economy for PHEV running in charge sustaining mode for the model year and vehicle type
MPkWh is the miles of travel per kilowatt-hour for PHEV running on battery charge for the model year and vehicle type
33.7 is the conversion factor used by the EPA to convert electrical energy to gasoline gallon equivalents[20]
Eprop is the proportion of DVMT driven on stored electricity calculated as follows:

$$Eprop = Range / DVMT$$

where:
Range is the average battery range for the model year and vehicle type
DVMT is the average daily vehicle miles traveled estimated for the vehicle. Where the range exceeds the DVMT of the vehicle, the value of *Eprop* is set to 1.

This formula uses a shortcut method to estimate *Eprop* in order to reduce execution time. It is adequate for the purpose of optimizing the assignment of household vehicle DVMT proportions to vehicles. A more thorough calculation of the proportion of DVMT powered by electricity occurs at a later step and is explained below.

Figure 53 shows the effect on overall fleet fuel efficiency of different optimization levels. This example assumes a future condition in which the average PHEV battery range is 40 miles and the PHEV market share grows to be 60% of autos and 30% of light trucks. It can be seen that optimization by all households with this condition reduces total fuel consumption by about 12 percent.

EVs are assigned from the PHEV/EV vehicles. This is done because the pool of potential EV owners is likely to be similar to the pool of PHEV owners, but whether or not a potential buyer chooses an EV rather than a PHEV will likely depend on how well the EV battery range matches up with the desired vehicle travel patterns. If the daily vehicle use routinely exceeds the battery range of an EV (assuming all EVs can be fully charged at night), then it is unlikely that a household would choose an EV over a PHEV. This interplay between EV range and vehicle DVMT is important to capture in the model. This is illustrated in Figure 54. The figure shows the proportions of total household DVMT traveled in vehicles that travel no more than the daily mileage thresholds shown on the x-axis. (This figure was tabulated from the NHTS dataset.) Separate response curves are plotted for households living in areas having different densities. For example, about 20 per cent of all DVMT for households living in areas with density of 50 persons per square mile is traveled in vehicles driven no more than 50 miles in a day. For

[20] EPA, Office of Transportation and Air Quality, Regulatory Announcement: New Fuel Economy and Environment Labels for a New Generation of Vehicles. https://www.epa.gov/fueleconomy

A gallon of gasoline stores 115,000 BTUs of energy. That is equivalent to 33.7 kWh.

households living in areas with a density of 7,000 persons per square mile, that proportion climbs to about 35 per cent.

FIGURE 53. EFFECT OF VEHICLE USE OPTIMIZATION ON FLEET AVERAGE MPG AND TOTAL FUEL CONSUMPTION

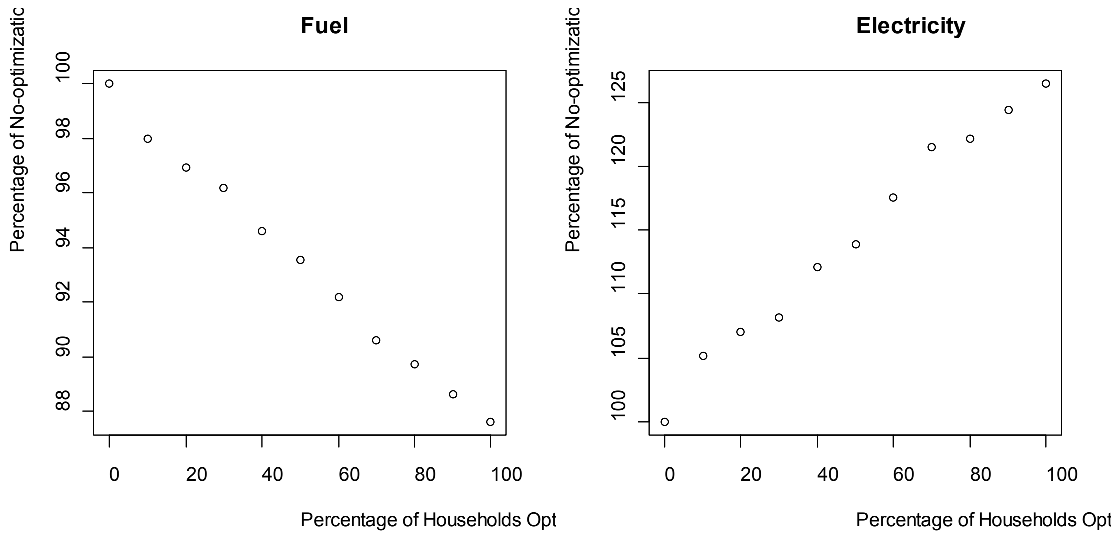
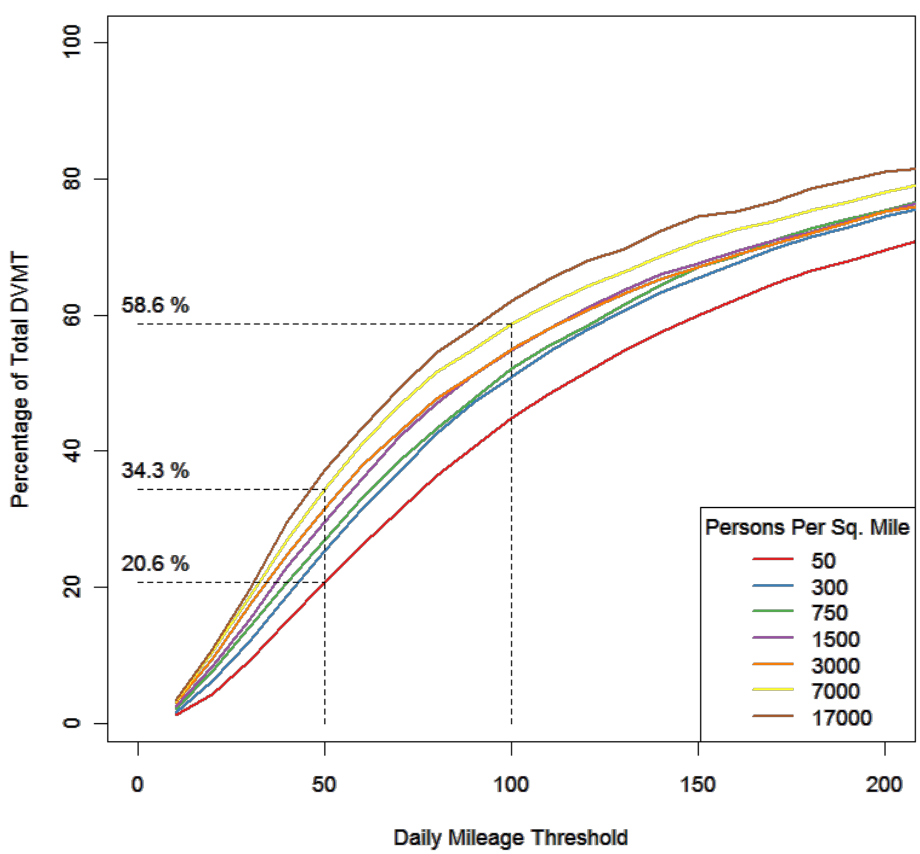


FIGURE 54. VEHICLE RANGE VS. PROPORTION OF TRAVEL



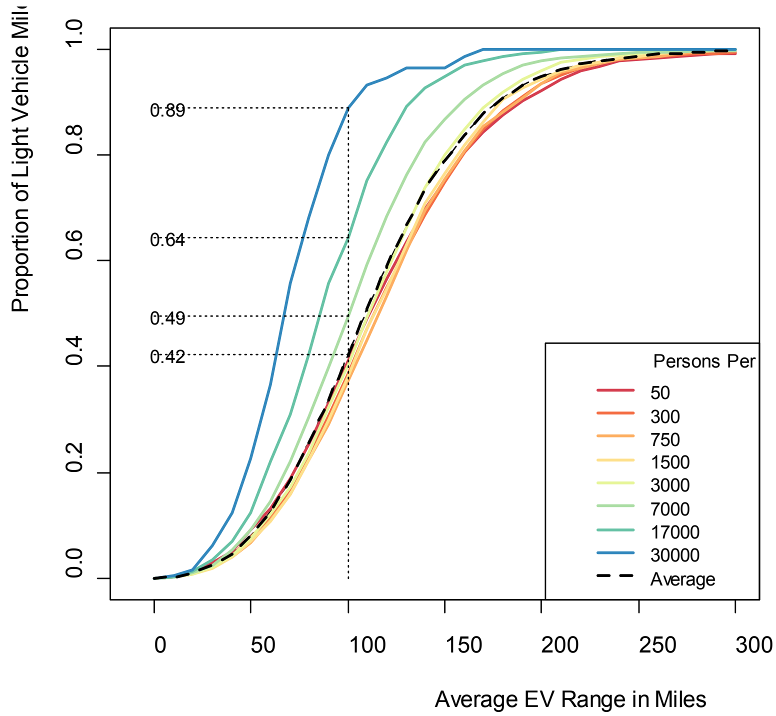
The approach taken is to compare the assumed EV travel range that is input to the model with the use characteristics of household vehicles. A household vehicle will be a candidate to be an EV if the 95th percentile DVMT of the vehicle is not greater than the EV battery range for the vehicle type and model year. It is assumed that for the other 5% of days, the household will be willing to adjust their trips, or car allocation, or may rent a car.

The EV travel range depends on the range that an EV can travel on a charge and the availability of EV charging stations. Without an extensive EV charging network, the EV range is effectively the range that an EV can run on a battery that is fully charged after an overnight charging at home. The EV range is lengthened if there is an extensive charging system that permits easy recharging of the EV during the day. These considerations need to be addressed in the development of the input assumptions to the EV model.

The other input to the EV model is the expected market penetration of electric vehicles among the candidate population. For example, a value of 0.5 means that 50 per cent of combined category of PHEVs and EVs are expected to be electric vehicles. This proportion is used as a sampling probability in a Monte Carlo process to assign EVs from the pool of EV candidates. Input assumptions for range and market penetration vary by vehicle type (auto, light truck) and model year.

This approach makes the model estimates of the amount of travel using electricity vs. fossil fuels sensitive to factors that affect the demand for household travel in addition to being sensitive to technological factors. Figure 55 shows the proportion of vehicle travel powered by electricity using the 95th percentile criterion and assuming 100% market penetration for all candidate vehicles. The figure illustrates the advantage of modeling EV ownership and usage within an interconnected modeling design. Factors like population density which reduce household vehicle travel also affect the potential for EV ownership and usage. The approach accounts for those effects.

FIGURE 55. TRAVEL USING ELECTRICITY BY AVERAGE EV RANGE AND POPULATION DENSITY USING 95TH PERCENTILE CRITERION AND ASSUMING 100% MARKET PENETRATION



Calculating the Proportions of PHEV Travel Powered by Electricity

The proportion of a household's PHEV mileage that would be powered by electricity will depend on the household's driving patterns. Some days the miles driven will be less than the range of the battery. On those days, all of the mileage will be powered by electricity. Other days, the mileage driven will exceed the range of the battery. On those days, the mileage powered by electricity will equal the battery capacity and the remainder of the miles will be powered by gasoline or other hydrocarbon fuel. Several assumptions are necessary in order to do the calculation:

1. Every PHEV in the future will have a strong electric motor that enables the vehicle to operate on electricity over its entire speed range subject only to the charge available in its batteries.[21]

2. All PHEVs will be recharged at home so that they will have a full battery charge at the beginning of the travel day.

3. On days when the total travel of the vehicle is less than the range of the vehicle, all vehicle travel will be powered by stored electrical energy.

[21] The Chevy Volt for example is driven by electric motors. The on-board internal combustion engine powers an electric generator which recharges the vehicle's batteries.

4. On days when the total travel of the vehicle is greater than the range of the vehicle, travel up to the range of the vehicle will be powered by stored electrical energy and the remainder will be powered by electricity generated by the on-board generator.

Given these assumptions, the calculation of the mileage a PHEV travels using stored electricity depends on two things: 1) the total DVMT for the vehicle traveled on days when the mileage for the day is less than the vehicle's battery range; 2) the number of days when the mileage for the day is greater than the vehicle's battery range. The total DVMT powered by stored electricity is therefore:

$$DVMT1 + Days2 \times Range$$

Where:
DVMT1 = Sum of DVMT on days when the daily mileage is less than the range
Days2 = Number of days when the daily mileage is greater than the range

In order to model these values, it was necessary to develop distributions of vehicle travel by vehicle for each household in the model estimation dataset. This was done with simulation as follows. For each household, the household DVMT for any particular day is calculated using the DVMT models described in a previous section. Since these are stochastic models, the results are different each time the model is run. The household DVMT is split among household vehicles using a stochastic process with sampling distributions of the split of household DVMT among household vehicles derived from the survey data. Figure 56 shows these sampling distributions for four vehicle ownership categories (1 vehicle, 2 vehicles, 3 vehicles, 4 or more vehicles). Each chart is a histogram showing the relative proportion of vehicles by the proportion of household DVMT traveled by the vehicle.

The combination of predicting household DVMT and proportioning the DVMT was run 400 times for each household to develop distributions of vehicle DVMT. Then using the equation above, the proportion of DVMT that would be powered by stored electricity was calculated at 5 mile range intervals starting at 5 miles and ending at 150 miles. This calculation was done for each household and the results were saved.

After the electrically powered travel proportions were calculated through simulation, linear models were estimated to predict the proportions at every range value. All the models have the same variables but the coefficients vary with the range. The coefficients are statistically significant at better than the 0.1% level for all ranges. As with many other parts of the GreenSTEP and RSPM models, separate models were estimated for metropolitan and non-metropolitan households. Table 63 shows an example of the model form and estimation statistics for a 10 mile PHEV range.

Figure 57 shows the coefficients for the metropolitan models. Figure 58 shows the corresponding coefficients for the non-metropolitan models.

FIGURE 56. DISTRIBUTION OF VEHICLE MILEAGE PROPORTIONS BY NUMBER OF HOUSEHOLD VEHICLES

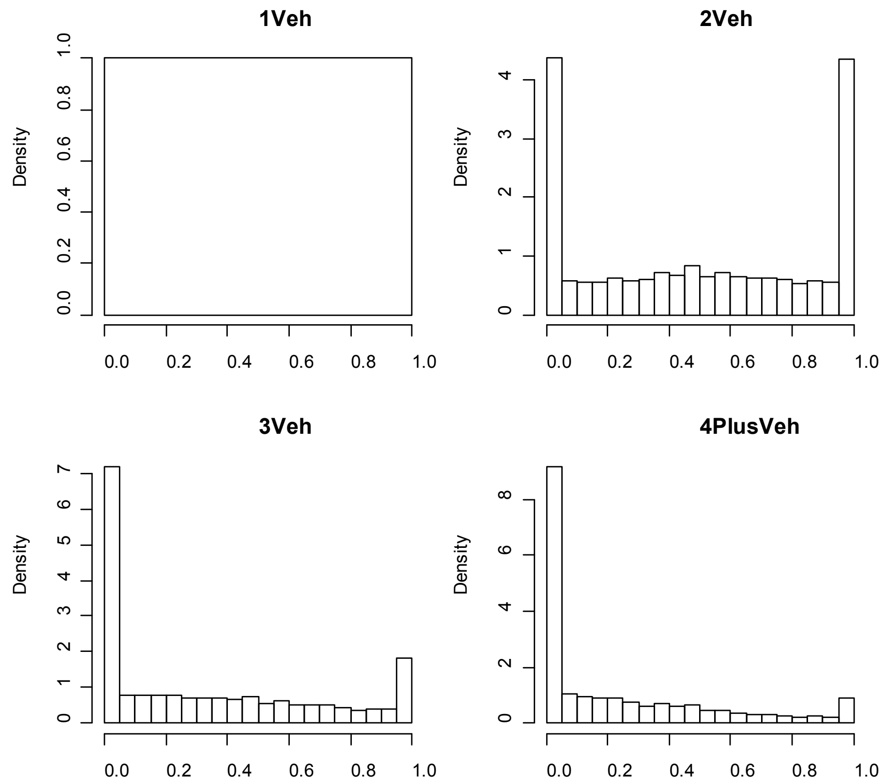


TABLE 63. MODEL OF THE PROPORTION OF TRAVEL POWERED BY ELECTRICITY FOR A PHEV HAVING A 10-MILE BATTERY RANGE FOR METROPOLITAN HOUSEHOLDS

```
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   6.641e-01  2.283e-03  290.81   <2e-16 ***
LogIncome    -4.350e-02  2.201e-04 -197.66   <2e-16 ***
Htppopdn      3.055e-06  2.799e-08  109.13   <2e-16 ***
Hhvehcnt      3.763e-02  1.779e-04  211.55   <2e-16 ***
Tranmilescap  2.926e-04  1.106e-05   26.46   <2e-16 ***
DrvAgePop    -2.954e-02  2.000e-04 -147.74   <2e-16 ***
Age65Plus     3.633e-02  2.244e-04  161.88   <2e-16 ***
Urban         2.521e-02  4.595e-04   54.87   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01898 on 17674 degrees of freedom
Multiple R-squared: 0.8946,   Adjusted R-squared: 0.8946

F-statistic: 2.143e+04 on 7 and 17674 DF,  p-value: < 2.2e-16
```

FIGURE 57. COEFFICIENTS OF METROPOLITAN PHEV ELECTRIC TRAVEL PROPORTIONS MODELS

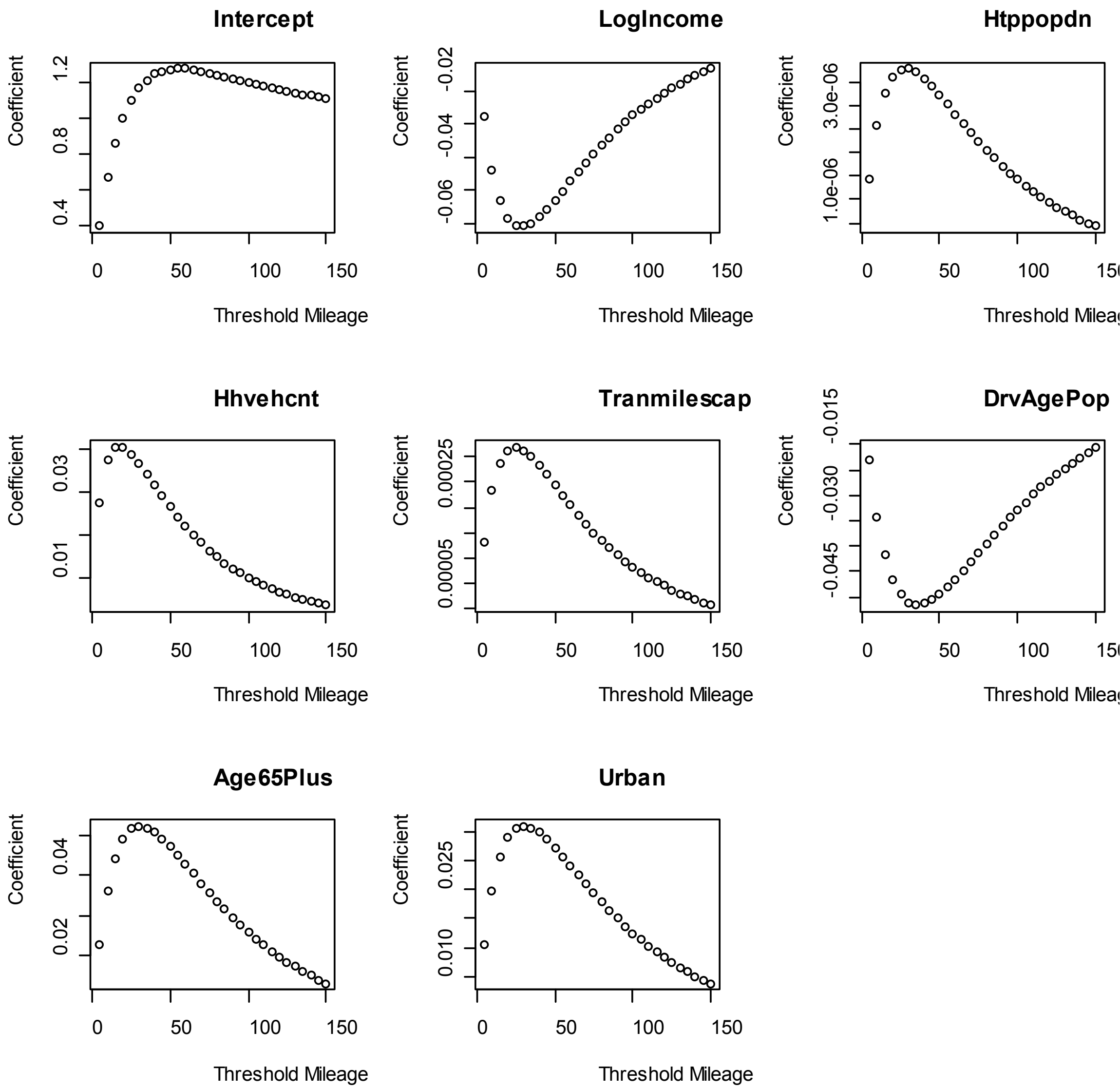
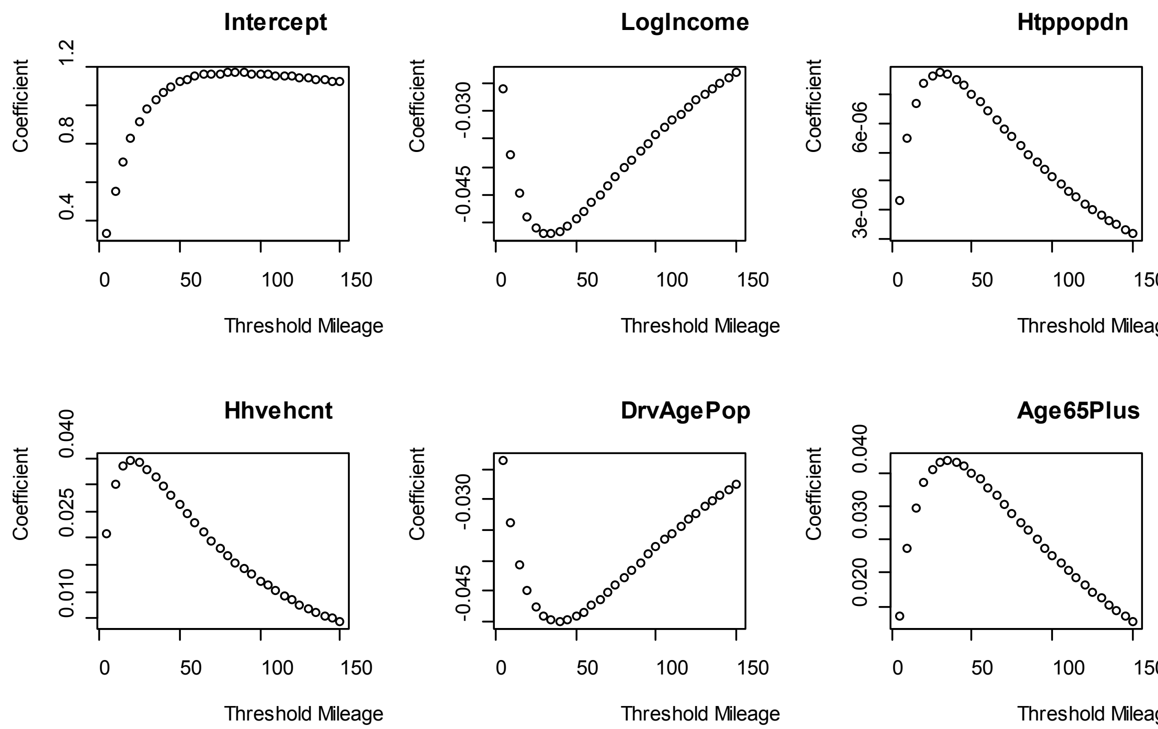


FIGURE 58. COEFFICIENTS OF NON-METROPOLITAN PHEV ELECTRIC TRAVEL PROPORTIONS MODEL



Since linear models of proportions can produce values less than 0 or greater than 1, the function to implement the models caps values at those levels. This adds a small, but unimportant distortion to the results. Figures 59 and 60 compare simulated (abscissa) values and modeled (ordinate) values for the metropolitan and non-metropolitan households respectively.

FIGURE 59. METROPOLITAN HOUSEHOLD SIMULATED AND MODELED PHEV ELECTRIC TRAVEL PROPORTIONS BY BATTERY RANGE

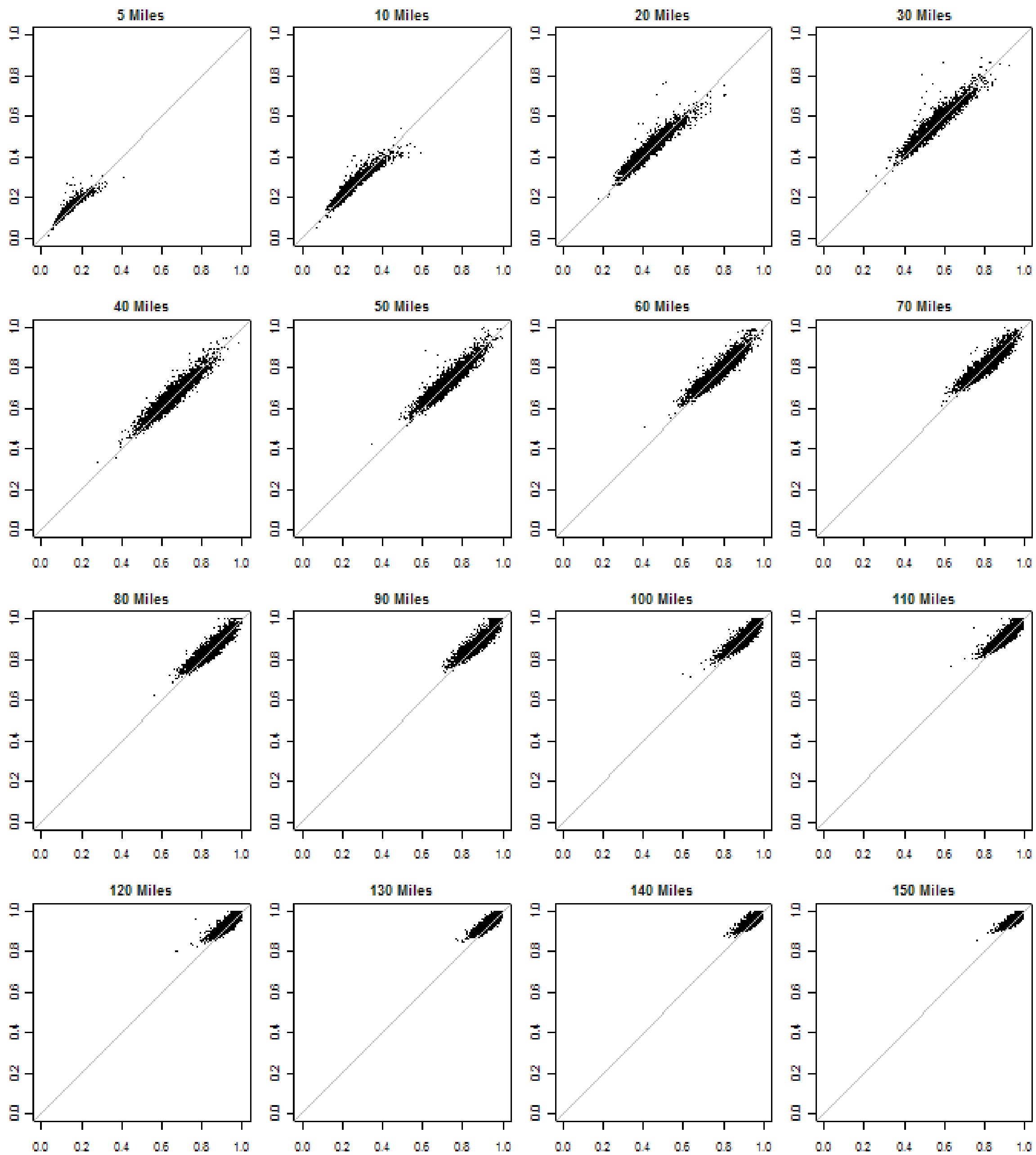


FIGURE 60. NON-METROPOLITAN HOUSEHOLD SIMULATED AND MODELED PHEV ELECTRIC TRAVEL PROPORTIONS BY BATTERY RANGE

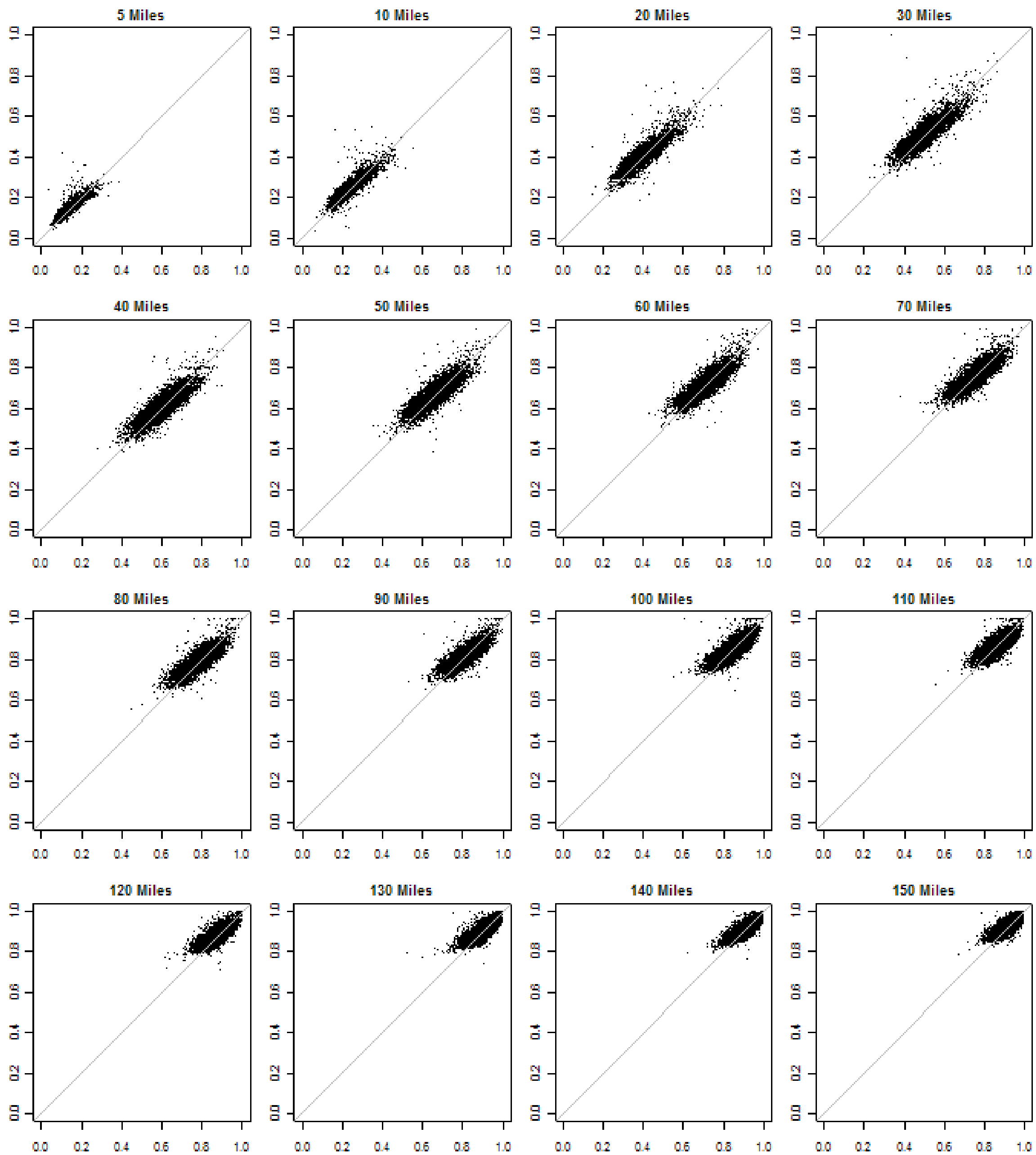
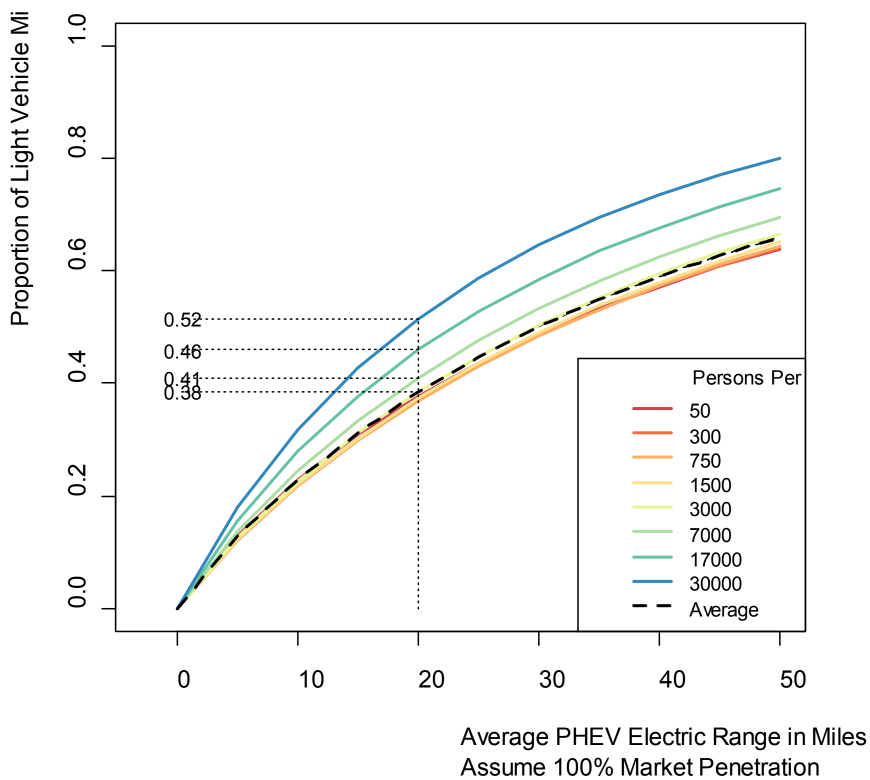


Figure 61 shows the results of testing the model using the metropolitan household data. As can be seen, the proportion of travel powered by stored electricity is sensitive to population density as well as the range of the vehicle. This model as well as the EV model will be sensitive to any factor which affects household DVMT

FIGURE 61. AVERAGE PROPORTION OF TRAVEL USING STORED ELECTRICITY BY PHEV BATTERY RANGE ASSUMING 100% MARKET PENETRATION



Once the electrically powered proportion of a household's PHEV mileage has been determined, that is used to calculate the DVMT that is powered by electricity and the DVMT that is powered by hydrocarbon fuels (e.g. gasoline).

Calculating Fuel Consumption, Electric Power Consumption and Greenhouse Gas Emissions

The amounts of fuel consumption, electric power consumption and greenhouse gas emissions for each household are straightforward calculations given that the DVMT, fuel economy, electric power efficiency, and electrically-powered proportion of DVMT has been determined.

Average daily fuel consumption for each vehicle that is not wholly electrically powered is calculating by dividing the average DVMT by the vehicle fuel economy. Since fuel economy is expressed in gasoline-equivalent gallon terms, fuel consumption is in gas equivalent gallons. For PHEVs, the DVMT used in the calculation is the DVMT that is powered by hydrocarbon fuels.

Average daily electrical power consumption is calculated similarly. For EVs it is the average DVMT of the vehicle divided by the energy efficiency of the vehicle (MPkWh). For PHEVs the DVMT used in the calculation is the DVMT that is powered by electricity.

After the fuel consumption and electricity consumption has been calculated for each vehicle, the respective totals are computed for each household. Greenhouse gas emissions are then calculated based on the carbon intensity of the fuel consumed and electricity consumed.

Carbon intensity is a measure of the weight of carbon dioxide equivalents produced per unit of energy consumed. Although carbon dioxide (CO_2) is the predominant greenhouse gas emission from the burning of transportation fuels (95%-99% of the total), small amounts of other greenhouse gases including methane (CH_4) and nitrous oxide (N_20) are produced as well. These gases are more potent greenhouse gases than carbon dioxide. In order to simplify and standardize comparisons, greenhouse gas emissions are expressed in carbon dioxide equivalents (CO_2e). The carbon intensity varies with each fuel and is expressed in grams of CO_2e per megajoule (MJ). One gallon gas contains about 132 MJ of potential energy.

Carbon intensity varies by energy source. It also varies with respect to whether the CO_2e estimates include the indirect emissions from producing the fuel as well as the direct emissions from using (i.e. combusting) the fuel. The direct emissions from fuel combustion are also referred to as tank-to-wheels (TTW) emissions. Emissions estimates which include emissions from production as well as combustion are referred to as life cycle emissions or as well-to-wheels (WTW) emissions. The GreenSTEP and RSPM models can calculate emissions either way depending on whether the carbon intensity values that are input to the model reflect WTW estimates or only TTW estimates. Studies using these models in Oregon have been using life cycle estimates of carbon intensity. This is consistent with other state agency policies and accounting processes. Table 64 shows the values that have been used in Oregon. The “Light Vehicle Composite” values will be explained in more detail below.

The estimates do not include indirect land use change effects of fuel production. Indirect land use change effects are primarily a concern relating to biofuels. Biofuel production from food crops or non-food crops that are grown on agricultural land can lead to the conversion of natural lands such as rainforests and grasslands that store carbon. Converting those lands to biofuel production or food production to replace cropland lost to biofuel production releases carbon dioxide into the atmosphere by removing the vegetation. It also diminishes the ability of those lands to sequester carbon. The net effects of biofuels on CO2e emissions are very difficult to estimate because they depend on the types of plant materials used to produce biofuels (whether they are grown for the purpose or whether they are bi-products of food crop production), the structure of agricultural product markets, regional land markets, etc. There is considerable debate about the magnitude of indirect land use effects. They are not included in the carbon intensity input values shown in Table 64 because Oregon has not come up with agreed upon numbers.

TABLE 64. CARBON INTENSITY BY FUEL TYPE (GRAMS CO_2E PER MJ)

Year	Ultra-low Sulfur Diesel	Biodiesel	Gasoline	Ethanol	Natural Gas	Light Vehicle Composite
1990	90.2	15.91	90.1	64.82	71.41	90.12
1995	90.2	15.91	90.1	64.82	71.41	90.11
2000	90.2	15.91	90.1	64.82	71.41	89.49
2005	90.2	15.91	90.1	64.82	71.41	90.24
2010	90.2	15.91	92.34	63.37	71.41	90.38
2015	90.2	15.91	92.34	63.37	71.41	89.48
2020	90.2	15.91	92.34	63.37	71.41	84.51
2025	90.2	15.91	92.34	63.37	71.41	78.63
2030	90.2	15.91	92.34	63.37	71.41	74.11
2035	90.2	15.91	92.34	63.37	71.41	72.3
2040	90.2	15.91	92.34	63.37	71.41	72.3
2045	90.2	15.91	92.34	63.37	71.41	72.3
2050	90.2	15.91	92.34	63.37	71.41	72.3

The GreenSTEP and RSPM models provide two options for calculating the carbon intensity of fuels consumed for light-duty vehicle travel. The simplified method uses a composite fuel type which represents a weighted average of all fuels used. Present and past intensity values for this composite fuel are calculated as a weighted average of the carbon intensity of each fuel weighted by the amounts consumed of each fuel. Future values can reflect scenario assumptions regarding regulations and/or objectives for reducing the average carbon content of fuels. This has been the approach for using GreenSTEP in Oregon to date. Table 64 illustrates an assumed overall decline in fuel carbon intensity of 20% between 2010 and 2035. The other method uses input estimates and assumptions regarding the mix of fuel types. Table 65 shows an example. (Note that the gasoline proportion is calculated as a remainder.) The model then computes weighted average carbon intensity from these numbers and the carbon intensities of the individual fuel types.

TABLE 65. EXAMPLE OF LIGHT-DUTY VEHICLE FUEL INPUTS

Year	Auto Proportion Diesel	Auto Proportion CNG	Lt. Truck Proportion Diesel	Lt. Truck Proportion CNG	Gas Proportion Ethanol	Diesel Proportion Biodiesel
1990	0.007	0	0.04	0	0	0
1995	0.007	0	0.04	0	0	0
2000	0.007	0	0.04	0	0	0
2005	0.007	0	0.04	0	0.1	0.01
2010	0.007	0	0.04	0	0.1	0.05
2015	0.007	0	0.04	0	0.1	0.05
2020	0.007	0	0.04	0	0.1	0.05

The household GHG emissions from fuel consumption are calculated by applying the average fuel carbon intensity calculated by either of the methods to the gallons of fuel consumed by the household as follows:

$$GHG = Gallons \times CI \times MJPerGallon \div 1e6$$

where:
GHG is the metric tons of CO2e emissions per day
Gallons is the daily consumption of fuel in gasoline-equivalent gallons
CI is the average carbon intensity in grams of CO2e per megajoule (MJ)
MJPerGallon is the energy content of gasoline in megajoules (132)
1e6 is a factor to convert grams into metric tons

The emissions from electric vehicles are also evaluated on a life-cycle basis. Even if the electricity that is consumed comes from out-of-state power plants, the emissions generated from those power plants are included in the calculation. The emissions rates are specified as pounds of CO2e per kilowatt-hour (kWh) at the end user location. Therefore, the rates reflect transmission line losses. These rates need to be specified by county and year in the input file. This is the case because there are a number of different power providers in Oregon that have different power generation portfolios (e.g. coal, natural gas, hydro, wind, solar). The rates for each county reflect the portfolio of each provider and the customer base of each provider in each county. Table 66 shows an excerpt of inputs for a scenario.

TABLE 66. EXAMPLE OF CARBON INTENSITY INPUTS FOR ELECTRICITY FOR A SELECTION OF COUNTIES AND YEARS (POUNDS CO_2E PER KILOWATT-HOUR)

County	1990	1995	2000	2005	2010	2015	2020
Baker	0.079	0.079	0.079	0.079	0.079	0.079	0.078
Benton	1.558	1.558	1.558	1.558	1.521	1.367	1.213
Clackamas	1.402	1.402	1.402	1.402	1.365	1.231	1.096
Clatsop	1.87	1.87	1.87	1.87	1.825	1.633	1.441
Columbia	0.086	0.086	0.086	0.086	0.086	0.085	0.084
Coos	1.495	1.495	1.495	1.495	1.459	1.313	1.167
Crook	1.423	1.423	1.423	1.423	1.389	1.252	1.114
Curry	0.079	0.079	0.079	0.079	0.079	0.079	0.078
Deschutes	1.127	1.127	1.127	1.127	1.101	1	0.898
Douglas	1.607	1.607	1.607	1.607	1.569	1.409	1.249
Gilliam	0.917	0.917	0.917	0.917	0.896	0.82	0.744

The household emissions from electricity consumption are calculated by applying the average carbon intensity for the county the household is located in to the amount of electricity consumed for vehicle travel as follows:

$$GHG = kWh \times CI \div 2204.62$$

where:
GHG is the metric tons of GHG emissions per day
kWh is the kilowatt-hours consumed per day for vehicle travel
CI is the carbon intensity of electricity production in pounds per kWh for the county the household is located in
2204.62 converts pounds to metric tons

Calculate Household Vehicle Costs and Revenues

The models calculate the following four types of costs stemming from household vehicle travel:

1. Costs for fuel and or electricity to run vehicles and variable use taxes;
2. Other costs of vehicle ownership and use that the household pays directly;
3. Road system costs; and,
4. External costs that are paid for by society as a result of the household's vehicle travel.

The first category includes fuel costs, electricity costs, gas taxes, mileage (i.e. VMT) taxes, congestion taxes, carbon taxes, pay-as-you-drive (PAYD) insurance, and parking pricing. The sum of these costs influences the amount of household travel in the household budget model. PAYD insurance costs and parking pricing are explained in more detail below.

The second category includes vehicle depreciation, vehicle maintenance, tires, finance charges, insurance, and registration. These costs primarily affect vehicle ownership and not vehicle use and therefore are not used in the household budget model to affect the household DVMT.

The third category includes costs for roadway expansion, other modernization projects, preservation, operations, maintenance and administration. These costs are used to compare with total vehicle use taxes (e.g. gas, mileage, congestion) to determine whether sufficient revenues are generated to cover costs.

The fourth category includes social and environmental costs that accrue to society but are not typically paid for by vehicle users. These costs include air pollution, climate change, energy security, safety, noise, and other resource impacts. Social costs are calculated on a per VMT, per gallon, or per metric ton of CO_2 basis so that they can be added to other taxes for scenarios in which it is assumed that full costs will be paid.

The cost rates, except for PAYD insurance and parking pricing, are specified in a table that is an input to the model (costs.csv). The following fields are included in the table:

- Year – scenario year

- FuelCost – average fuel cost in dollars per gallon
- KwhCost – average cost of electricity in dollars per kWh
- VmtTax – mileage tax in dollars per vehicle mile
- CarbonTax – tax on carbon emissions in dollars per metric ton
- GasTax – tax on fuel sales in dollars per gallon
- AirPollution – external cost of air pollution in damage to public health, buildings/materials, agriculture/forestry and ecosystems (exclusive of climate change) in dollars per mile
- OtherResource – external cost of other resource damage (e.g. soil and water pollution) in dollars per mile
- ClimateChange – external cost of climate change impacts due to greenhouse gas emissions in dollars per metric ton
- EnergySecurity – economic costs of petroleum dependence in dollars per gallon

Pay-as-You-Drive Insurance

PAYD insurance is automobile insurance that is paid strictly on a mileage traveled basis, rather than on a lump-sum periodic basis. On average, PAYD insurance does not change the amount that households pay for insurance. However, since the cost of PAYD to the motorist varies with the number of miles driven, there is an incentive to reduce travel to save money. It has been estimated that a PAYD insurance rate of 4 to 6 cents per mile, could reduce VMT from light vehicles by about 3.8%.[22] These estimates of the effect of PAYD insurance are on based on assumptions about the price elasticity of vehicle travel. The right elasticity value to use is uncertain.[23] Since the GreenSTEP and RSPM models treat variable costs as a budget effect, price elasticity depends on the sum of all variable costs, and therefore the estimated effect of PAYD insurance will depend on what other costs are being paid as well.

Table 67 shows the result of modeling PAYD insurance as a variable cost using the budget approach (explained below). Insurance rates of from 1 cent to 10 cents per mile were modeled at three different gas price levels. The percentage reduction in DVMT increases as the PAYD rate increases and as the fuel price increases.

In previous versions of the GreenSTEP and RSPM models, the probability that a household would be assigned PAYD insurance would be equal to the proportion of households to be assigned PAYD insurance. In other words, the characteristics of the household would not influence its likelihood of being chosen for PAYD insurance. This has been changed in Version 3.5. A simple method was devised to assign weights to households to influence the likelihood that a household is chosen for PAYD insurance based on its characteristics. Household PAYD propensity weights are assigned based on the presence of teenagers, whether the average

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[22] U.S. Department of Transportation, Report to Congress, Transportation's Role in Reducing U.S. Greenhouse Gas Emissions, Volume 2: Technical Report, April 2010, pp. 5-22.

[23] U.S. Department of Transportation, Report to Congress, Transportation's Role in Reducing U.S. Greenhouse Gas Emissions, Volume 1: Synthesis Report, April 2010, pp. 3-15.

annual vehicle mileage for the household is low, whether drivers are older, whether household income is relatively low, and whether their vehicles tend to be autos rather than light trucks. The likelihood that household is selected is directly proportion to the weight assigned to the household. In order for a household to qualify for PAYD insurance, all household vehicles must be a 1996 or later model year since earlier model year vehicles don't have the electronics port needed for the PAYD monitoring equipment. If the target proportion of PAYD households is greater than the proportion of qualifying households, the result will be the qualifying households. Each qualifying household is initially assigned a weight of one point. Additional points are assigned additional points as shown in Table 68. The likelihood that a household is selected is proportional to the total weight calculated for the household.

TABLE 67. ESTIMATED PERCENTAGE REDUCTION IN HOUSEHOLD DVMT AT VARIOUS PAYD INSURANCE RATES AND GAS COST LEVELS

PAYD Rate (cents/mile)	Base Gas Cost	2 X Base Gas Cost	3 X Base Gas Cost
1	0.0	0.0	0.0
2	0.2	0.6	1.1
3	0.4	1.3	2.3
4	0.6	2.0	3.6
5	1.0	2.9	4.9
6	1.3	3.8	6.2
7	1.8	4.8	7.6
8	2.3	5.8	9.1
9	2.9	7.0	10.5
10	3.6	8.2	12.0

TABLE 68. HOUSEHOLD PAYD INSURANCE CHOICE WEIGHTS

Characteristic	Weight
One or more teenage drivers in household	3
Average annual vehicle mileage < 15,000	3
Older drivers in household	2 * proportion of drivers age 20 or older
Annual household income < $45,000	2
Proportion of automobiles	2 * proportion of vehicles that are autos

Parking Pricing

Parking pricing is a trip-based cost, commonly paid for at one or both ends of a trip, and sometimes paid for on a monthly basis. The standard practice for handling parking pricing in urban travel demand models is to include it in the trip costs for auto travel. The models handle parking pricing in a more general way. Two types of parking costs are addressed in the model - parking costs at places of employment and parking costs at other places. Daily parking costs are calculated for each household and added in with other variable costs.

For employer-based parking, the proportion of employees that pay for parking is a policy input for each metropolitan area. Employer-based parking includes parking provided at the employment site as well as parking in other parking facilities near the employment site. A related policy variable is the availability of free parking in the vicinity of employment sites. This is specified as the ratio of employment parking to available parking in the vicinity of employment sites. It is assumed that the proportion of employees who pay for parking is a function of the proportion of employers who charge for parking and the employment parking proportion of total parking available in the vicinity of employment sites. After the proportion of workers paying for parking has been calculated, the proportion of working age adults paying for parking is calculated using the labor force participation rate (0.65).

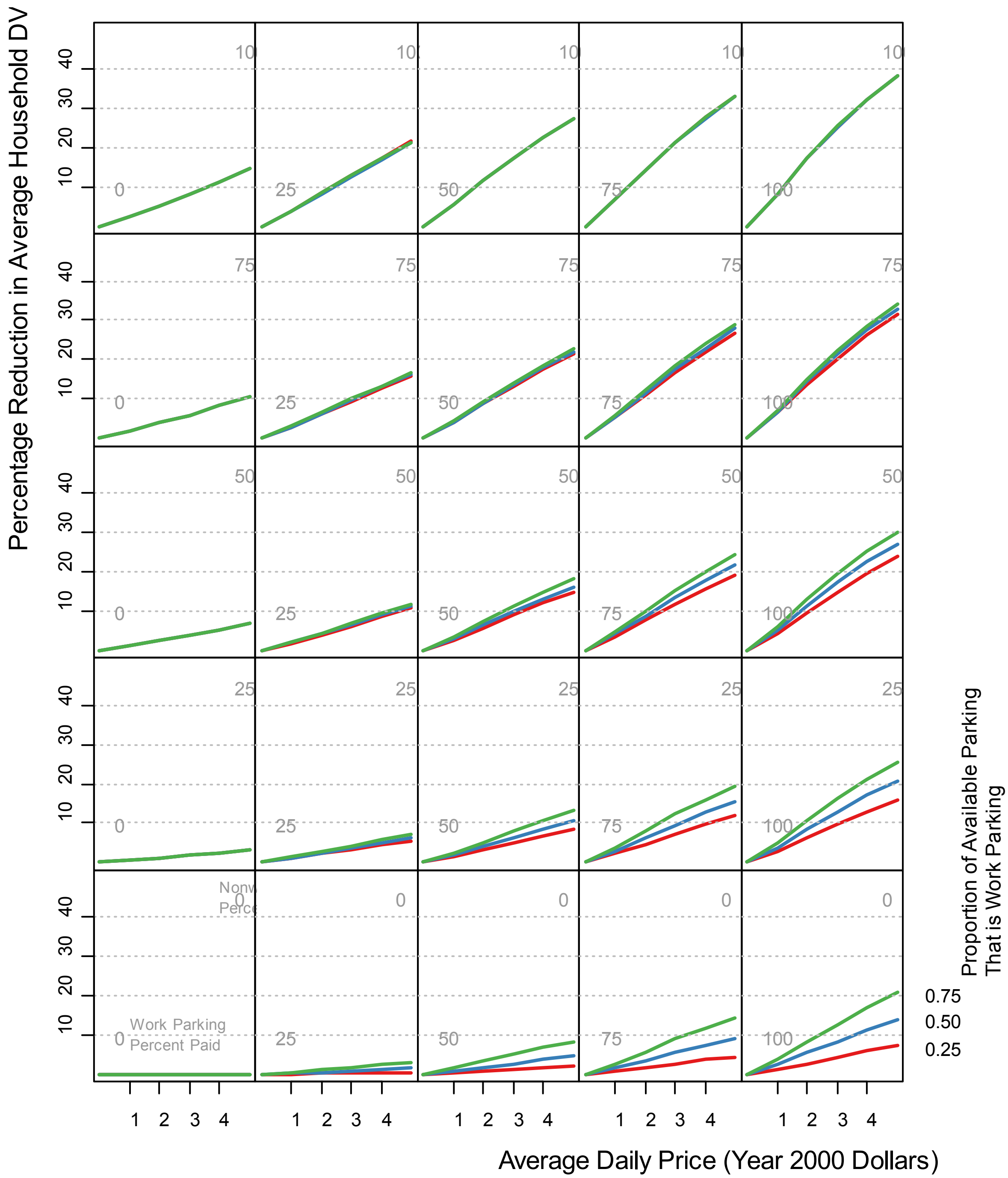
Another policy input is the proportion of employment parking that is converted from being free to being charged under a “cash-out buy-back” type of program. Under these programs all employees are charged for employer-provided parking but they are also provided with a stipend equal to the parking cost regardless of whether they use the parking or not. This provides an incentive for employees to carpool or use other modes of transportation to get to work.

The rate per working age adult and the proportion of “cash-out buy-back” parking are used in a Monte Carlo process to determine the number of adults in the household that have to pay for parking at their place of work and the number that pay through a “cash-out buy-back” program. Households are charged the daily parking rate for the number of working age persons identified as paying for parking. Their income is increased for the number of working age persons identified as participating in “cash-out buy-back” programs with the amount equal to the daily parking rate times the number of working days in a year (260).

Parking charges associated with non-work travel are specified in terms of the proportion of non-work vehicle trips that incur parking costs. The daily household parking cost for non-work travel is calculated as the proportion of non-work trips that incur a parking cost times the average proportion of DVMT that is for non-work travel (0.78) times the average daily parking cost.

Figure 62 shows the result of testing this model over a range of daily parking costs, percentages of employees paying for parking, percentages of non-work trips that incur a parking charge, and availability of free parking in the vicinity of employment sites. The graphs in the figure are laid out in a matrix where each column represents a percentage of workers paying for parking and each row represents a percentage of non-work trips that incur a parking charge. The percentage of workers paying for parking increases from left to right. The percentage of non-work trips incurring a parking charge increases from bottom to top. Each graph shows the response of the percentage reduction in average household DVMT as the average daily parking charge increases from 0 to 5 dollars. The three lines in each graph show three ratios of employment parking to total parking in the vicinity of employment sites.

FIGURE 62. RESPONSE OF PARKING MODEL TO CHANGES IN PARKING PRICES, PERCENTAGES OF WORKERS AND NON-WORK TRIPS INCURRING PARKING CHARGES, AND AVAILABILITY OF FREE PARKING IN THE VICINITY OF WORK SITES



Modeling the Effects of Vehicle Travel Costs on Household Vehicle Travel

The reader may have noticed that no costs are included in any of the household vehicle travel models. This is not an oversight. The effects of all variable vehicle costs on travel are handled by a household travel budget model described in this section.[24]

It is important that the GreenSTEP and RSPM models be able to reasonably account for the effects of fuel prices and similar variable costs such as fuel and carbon taxes on the amount of vehicle travel. There is a significant interest in using pricing mechanisms to affect the demand for vehicle travel, so we need a model to estimate what the effect of pricing might be. We also need to be able to account for the effect of future fuel price increases on vehicle travel.

This section describes the approach for incorporating prices into the models. It starts by summarizing previous approaches and explaining why those approaches were found to be deficient. It then describes the current approach which is based on household budgeting and presents information in support of that approach. Finally, it describes the approach in more detail, demonstrates the results of applying the approach, and compares the results with data from the Bureau of Labor Statistics' Consumer Expenditure Survey (CES).

Previous Approaches to Modeling Price Effects

It is a challenging endeavor to account for the effects of prices on travel in a long range model given:

1) The lack of disaggregate panel data that can be used to study how household travel decisions change over time in response to changes in prices;
2) The relatively low historical price of fuel;
3) The prospect for future prices that may be several times greater than present prices;
4) A lack of research consensus on the magnitude of the effects; and,
5) The difficulty of sorting out short range and long range effects.

Two methods were attempted prior to settling on the method described later in this section. The first method included in the original GreenSTEP production code, treated increases in fuel prices and other variable costs as an income effect. Cost was not explicitly included in the household VMT model. Instead, the increase in cost to the household as a result price increases over the year 2001 level, was subtracted from household income and then the model was rerun

[24] Variable vehicle costs are costs that vary with the amount of travel, not with the amount of vehicles owned.

with the adjusted income. This approach was used because of concerns at the time that there was insufficient data, and because variability in gas prices in the survey data was low.

This approach was abandoned after sensitivity testing showed that the model was very insensitive to prices, even very large prices such as $20/gallon gas prices. This insensitivity of travel to prices was found to be consistent with observed changes over the past decade reported by the Congressional Budget Office.[25] However, it would be unreasonable to expect the response to prices to be insensitive even at very high price levels. At some point a household will not be able to afford continued increases in fuel prices and there should be a significant travel response.

The second approach, also discarded, included the average gas price per mile of travel paid by households as an explicit variable in the household VMT model. Although most of the household records in the model estimation dataset did not include the fuel economy information needed to calculate the average cost per mile of travel for the household, enough household records did include this information to be able to estimate a model. The average gas cost per mile variable was found to be statistically significant in the estimated metropolitan and non-metropolitan models.

The resulting models were compared in aggregate against Consumer Expenditure Survey (CES) data. The CES estimates of the percentage of household income spent on gasoline provides good independent validation targets. These estimates are available for all households and for households by income group.

To do the validation test, the percentage of household income spent on gasoline was calculated for the household records in the estimation dataset that have fuel economy information. To do so, the average DVMT for each household record was estimated using the previously estimated average household DVMT models that included a gas cost per mile variable. These predictions were multiplied by 365 to estimate the annual DVMT for each household. The annual household DVMT was multiplied by the average gas cost per mile of travel for the household to estimate annual household expenditures for gasoline. The result for each household was divided by the household income to compute the proportion of the household's income spent on gasoline.

To compute comparable averages from the CES and the model results, averages were computed for households by the income categories reported by the CES. Modeled households were grouped using the income breaks reported by the CES and simple averages were computed for each income group. The overall average for the model population and the overall average for the CES data were computed by weighting the income group averages by the proportion of households in each income group as reported by the CES.

[25] U.S. Congressional Budget Office. *Effects of Gasoline Prices on Driving Behavior and Vehicle Markets.* Pub. No. 2883, the Congress of the United States, Congressional Budget Office, Washington, D.C. 2008.

Figure 63 shows how the average for all households in the estimation dataset compared with the overall average reported by the CES. The CES data show the values from 1992 to 2008, whereas the model estimate is only for the year 2001. As can be seen, the model estimate is close to the CES estimate for 2001.

Table 69 shows that the model and CES estimates for the year 2001 at the income group level also compare reasonably well.

FIGURE 63. COMPARISON OF THE PERCENTAGE OF HOUSEHOLD INCOME SPENT ON GASOLINE CALCULATED BY APPLYING THE GREENSTEP MODEL TO THE 2001 NHTS HOUSEHOLD DATA WITH THE PERCENTAGES REPORTED BY THE CONSUMER EXPENDITURE SURVEY

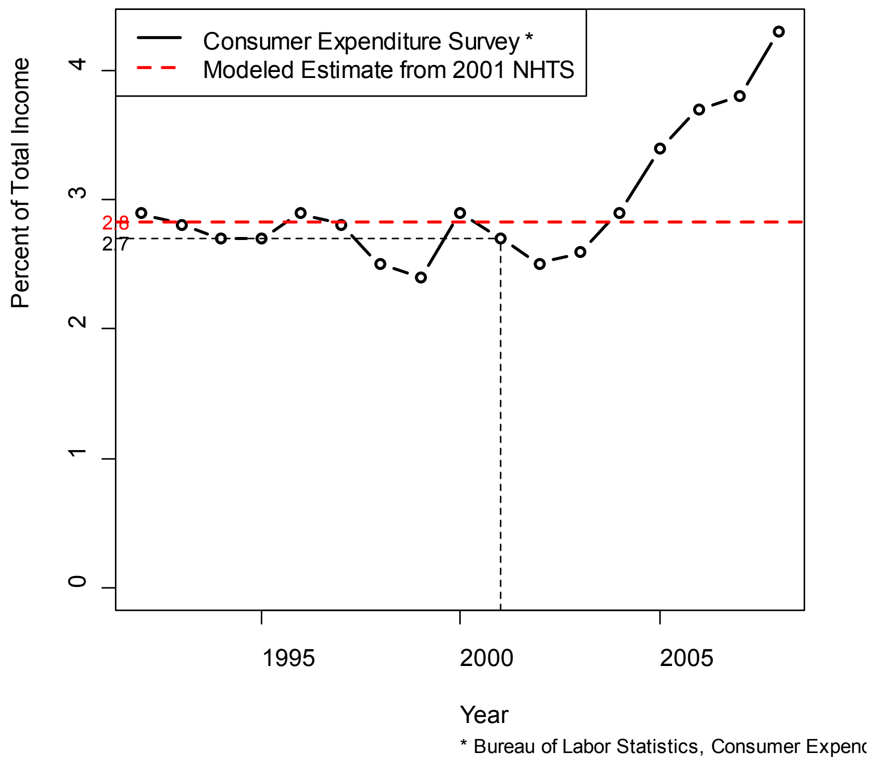


TABLE 69. COMPARISON OF MODEL ESTIMATION INCOME PERCENTAE SPENT ON GASOLINE BY INCOME GROUP WITH CONSUMER EXPENDITURE SURVEY ESTIMATES

	$0-$30K	$30K-$40K	$40K-$50K	$50K-$70K	$70K+
Model	5.0%	3.3%	2.9%	2.5%	2.0%
CES	5.2%	3.6%	3.3%	2.7%	1.8%
Model/CES	0.96	0.92	0.88	0.93	1.11

Although this model validated well against the CES information for the 2001 base year, it could not replicate the expenditure trend from 2001 to 2008 when gas prices were increasing.

The response of the model to increasing gas prices was tested by adjusting the average gas cost per mile of each household in the dataset to reflect changes in average gasoline costs and fuel economy from 2001. The adjustment factors are shown in Table 70.

Figure 64 shows the results of two sensitivity tests using this model. The plot on the left shows the results of running the travel demand model for each year with adjusted gasoline costs. The plot on the right shows the results of running the travel demand model with no change in gasoline cost (i.e. household average DVMT was calculated only at the 2001 price level). In both cases, the estimated amounts spent on gasoline for each year were calculated as described above using the adjusted gasoline costs per mile of travel. The model results, represented by the solid lines, are compared with the CES estimates, represented by the dashed lines.

TABLE 70. CALCULATION OF COST INDICES FOR ADJUSTING HOUSEHOLD COSTS TO REFLECT CHANGES IN GASOLINE PRICES

Year	Nominal Gas Cost[26]	Deflator	Inflation Adj. Gas Cost	Average MPG[27]	Average Cost Per Mile	Cost Index
2001	146.0	1	146.0	20.4	7.16	1
2002	138.6	0.98	136.4	20.3	6.72	0.93
2003	160.3	0.96	154.3	20.0	7.72	1.06
2004	189.5	0.94	177.7	20.1	8.84	1.22
2005	231.4	0.91	209.8	20.4	10.28	1.44
2006	261.8	0.88	230.0	20.7	11.11	1.58
2007	284.3	0.86	242.9	20.7	11.73	1.67
2008	329.9	0.83	271.4	20.8	13.05	1.86

It can be seen that the model results shown in the right-hand figure are much closer to the CES expenditure trends than the model results shown in the left-hand figure. The left-hand figure shows that although the model with a gas cost term validates well for the base year, it is much too sensitive to changes in the cost of fuel. The model predicted a significant attenuation in the amount of household travel due to rising fuel prices. The results shown in the right-hand figure clearly imply that rising fuel prices had little effect on household travel over the time period shown. This finding is consistent with the findings by the Congressional Budget Office and others[28].

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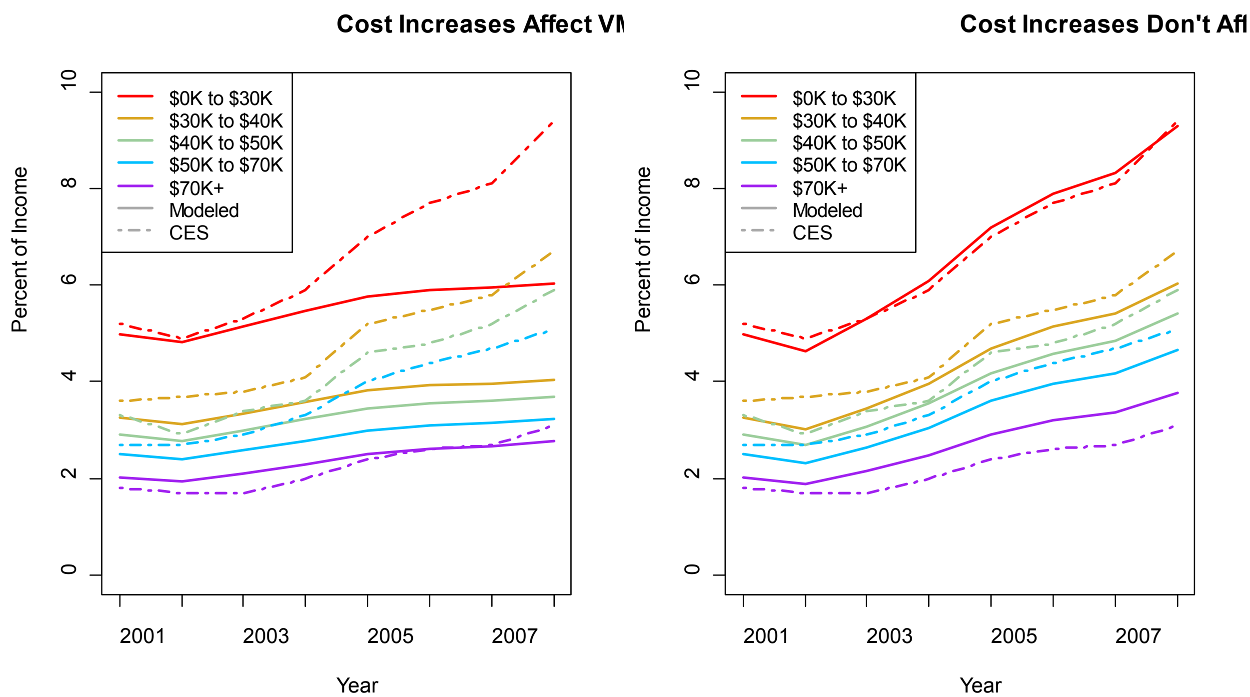
[26] U.S. Energy Information Administration, "U.S. All Grades All Formulations Retail Gasoline Prices (Cents per Gallon)"

[27] U.S. DOT, Federal Highway Administration, Highway Statistics annual publications, table VM-1. Average passenger fuel economy calculated as the average of passenger car and other 4-wheel passenger vehicles (e.g. van, pickup truck, SUV) weighted by the respective mileage.

[28] U.S. Congressional Budget Office. *Effects of Gasoline Prices on Driving Behavior and Vehicle Markets.* Pub. No. 2883, the Congress of the United States, Congressional Budget Office, Washington, D.C. 2008.

This test raised serious questions about the price sensitivity of a model that includes a fuel cost variable. Although the model appeared to accurately reflect the effects of prices on household behavior relative to other factors in 2001, it did a very poor job of reflecting the effects of changes in gasoline price over most of the past decade.

FIGURE 64. TIME SERIES TESTS COMPARING MODEL RESPONSE TO PRICE CHANGES WITH CONSUMER EXPENDITURE SURVEY



Both the income adjustment approach and the direct modeling approach for addressing the effect of prices on household vehicle travel demand were found to be unsatisfactory. While the income adjustment approach did a reasonable job of replicating changes in travel over the past decade in response to changes to fuel prices, it produced unreasonable results in response to large price changes. In contrast, the direct modeling approach greatly overestimated the effect of fuel price changes over the past decade on household vehicle travel.

Hughes, Jonathan E., Christopher R. Knittel, and Daniel Sperling. *Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand.* The Energy Journal, Vol. 29, No. 1. 2008.

Small, Kenneth A., and Kurt Van Dender. *Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect.* UC Irvine Economics Working Paper #05-06-03. August 18, 2007.

Given the failure of both of these approaches, a different approach had to be found. That approach is to model household vehicle travel in the context of a household travel budget.

Support for a Budget Approach in Consumer Expenditure Data

The budget approach to modeling is based on the perspective that households make their travel decisions within money and time budget constraints. This was fundamental to the work of Yacov Zahavi in the 1970s and early 1980s.[29] More recently, Michael Wegener has referred back to the work of Zahavi and proposed that models need to be based more on budget constraints and less on observed preferences.[30]

The basic model concept is as follows:

1) Household spending on gasoline and other variable costs is done within a household transportation budget that is relatively stable. Households shift expenses between transportation budget categories as needed.

2) As long as it is possible for the household to shift expenditures among components of the transportation budget, the household response to changes in fuel prices can be inelastic. However, when fuel prices or other variable costs increase to the point where it is no longer possible to shift money from other parts of the transportation budget, the household will necessarily reduce their travel in direct proportion to the cost increase (ceteris paribus).

3) The transition between inelastic and elastic behavior will not be abrupt unless there is little time for the household to recognize the impact of the cost increases on the budget or respond to the cost increases. If the changes are more gradual, the transition will be less abrupt.

Figure 65 shows that average household expenditures on transportation (in real dollars), reported by the CES, have remained fairly constant over the 25 year period from 1984 to 2008. In contrast, expenditures on housing, insurance and pensions, health, and entertainment increased, while expenditures on apparel decreased.

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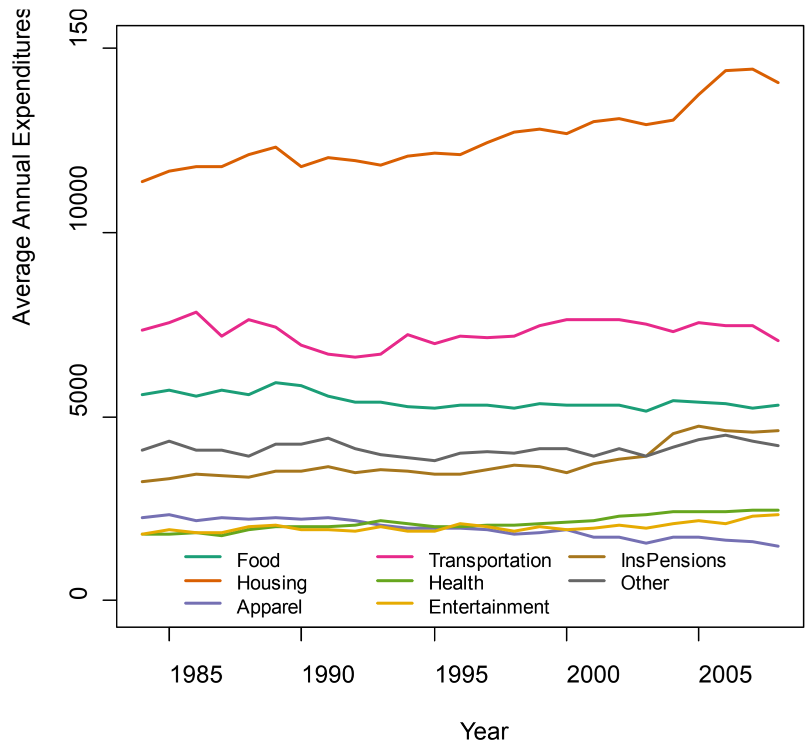
[29] See for example: Zahavi, Yacov, "The 'UMOT' Project", UDOT, Research and Special Programs Administration, Washington, D.C., August 1979 (http://www.surveyarchive.org/Zahavi/UMOT_79.pdf)

[30] Wegener, Michael, "After the oil age: Do we need to rebuild our cities?", 5th Oregon Symposium on Integrating Land Use and Transport Models, Portland Oregon, June 19-20, 2008.

FIGURE 65. AVERAGE HOUSEHOLD EXPENDITURES BY CATEGORY, 1984 - 2008



The CES disaggregates transportation expenditures into several components. The Major components are vehicle purchases, gasoline and motor oil, other vehicle expenses (e.g. maintenance, repair, insurance, licensing, leasing, finance charges), and public transportation. Figure 66 shows trends in average annual household expenditures in these categories from 1984 to 2008 in real (2001) dollars[31]. The chart also shows the national average gasoline price in real (2001) dollars.

Examination of the figure reveals several significant relationships between fuel prices and the amount of household spending on different components of transportation. First, it is quite striking that household expenditures on gasoline and motor oil track gasoline price trends very closely. This strongly implies that household gasoline consumption was relatively inelastic with respect to gasoline price over this period. Second, there was apparently a substantial amount of shifting of household expenditures between these components in response to fuel price changes. Expenditures for other vehicle expenses increased when gasoline expenditures declined and vice versa. The drop in vehicle purchase expenses over the recent period of fuel price increases is also quite striking. The household expenditure balancing can also be seen in Figure 67 which compares urban and rural household expenditures. Higher rural gasoline expenditures are offset by lower other vehicle expenses.

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[31] The total expenses on car purchases for all households in a given income group are averaged over all households in the income group to produce an average value.

FIGURE 66. AVERAGE HOUSEHOLD EXPENDITURES ON MAJOR TRANSPORTATION COMPONENTS, 1984 - 2008

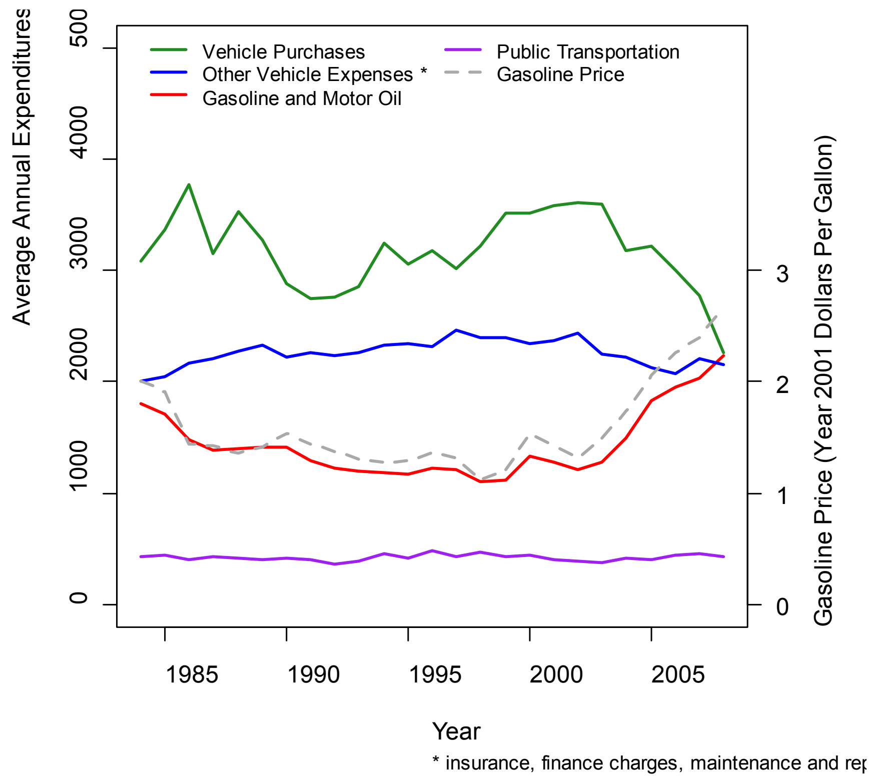
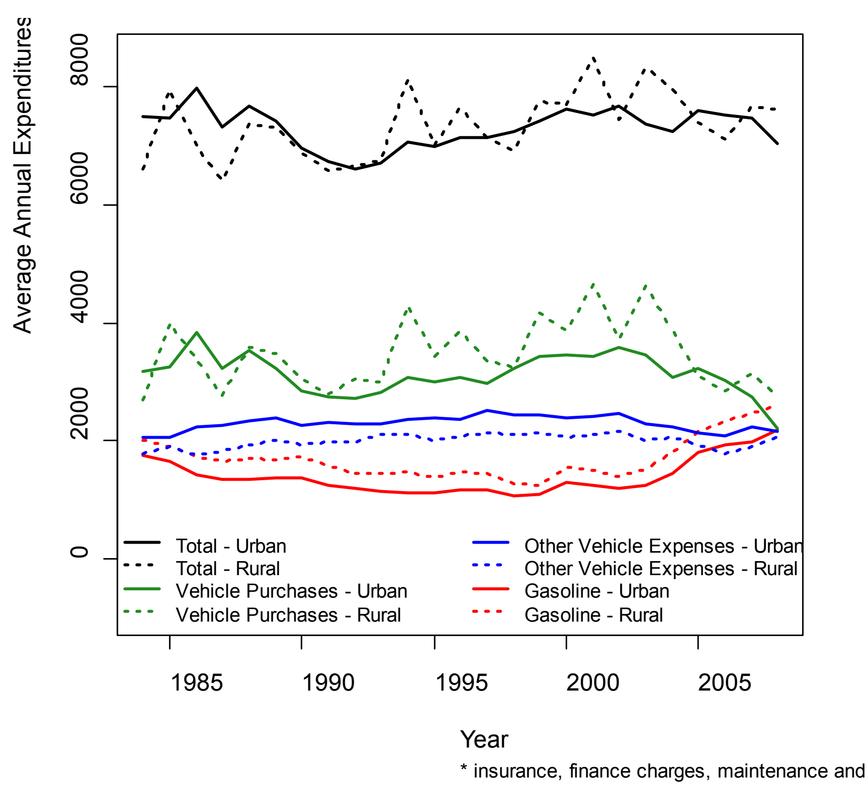


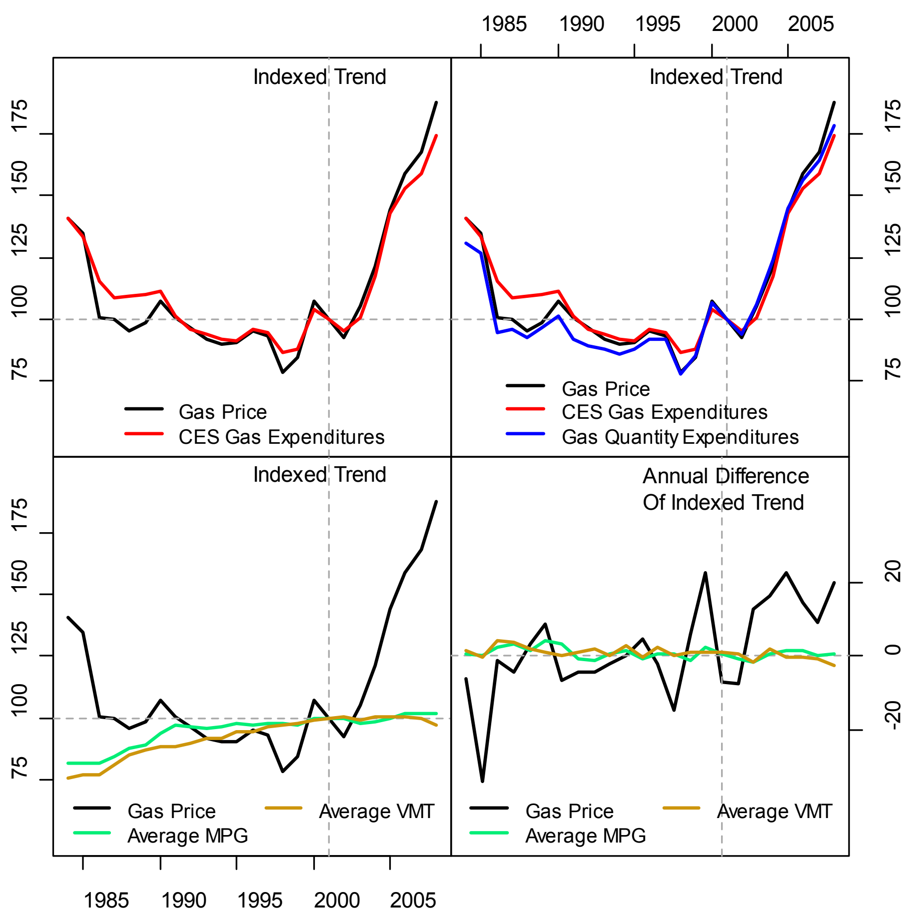
FIGURE 67. COMPARISON OF TRANSPORTATION EXPENDITURES OF URBAN AND RURAL HOUSEHOLDS



The relationship between gasoline prices, household gasoline expenditures, and household vehicle travel is explored further in several graphs shown in Figure 68. The top left panel of the figure overlays the gas price and CES gasoline expenditure trends from 1984 to 2008. Both trends are indexed to their 2001 levels to put them on the same scale and to enable proportional changes to be correctly compared. It is apparent that these trends track one another very closely. The correlation coefficient of the trends is 0.98.

The close relationship between gasoline prices and expenditures has significant implications for understanding the relationships between gasoline prices and vehicle travel. Clearly, rising fuel prices had very little effect on fuel consumption. This close relationship also strongly implies that fuel prices had little effect on VMT as well. The model test described previously gives support to that implication. But in order to establish whether fuel price changes have had much effect, if any, on VMT it is necessary to also examine how fuel economy and vehicle travel have changed over the same period. That is done in the remaining panels of Figure 68.

FIGURE 68. TRENDS IN GAS PRICES, GAS QUANTITY EXPENDITURES, AVERAGE MPG, AND AVERAGE VMT, INDEXED TO 2001 VALUES: 1984 - 2008



* Total quantity consumed divided by number of consuming

Since the CES does not include information about fuel economy or miles of vehicle travel, another source of information was needed to relate these quantities. One ready source is data published in “Highway Statistics”. Table VM-1 includes estimates of the numbers of vehicles, miles driven, and fuel economy by type of vehicle. Two types of personal passenger vehicles are reported; cars and other 4-wheeled passenger vehicles. The latter type includes pickup trucks, sport utility vehicles (SUV), and vans. From this information, along with real gasoline prices and the number of “consuming units” for the corresponding CES expenditure data, average gasoline expenditures and average VMT per “consuming unit” (i.e. household) can be calculated. The quantities calculated from these data are as follows:

- Average MPG for all passenger vehicles is calculated from the averages of each vehicle type by weighting vehicle MPG by type by the estimated mileage driven by each type.
- Average VMT per household is calculated by dividing total VMT by the number of consuming units reported in the CES.
- Average gasoline expenditure per household is calculated by dividing total passenger vehicle VMT by average MPG, multiplying the result by real gas prices, and dividing that result by the number of consuming units.

The top right panel of Figure 68 shows that the indexed trend for household gasoline expenditures calculated from the Highway Statistics data follows the CES data trend closely enough to enable meaningful evaluation to be done on the relationships between gasoline prices, gasoline expenditures, fuel economy, and VMT. Household gasoline expenditures calculated in this way are even more highly correlated with gasoline prices than is the case with the CES expenditure data.

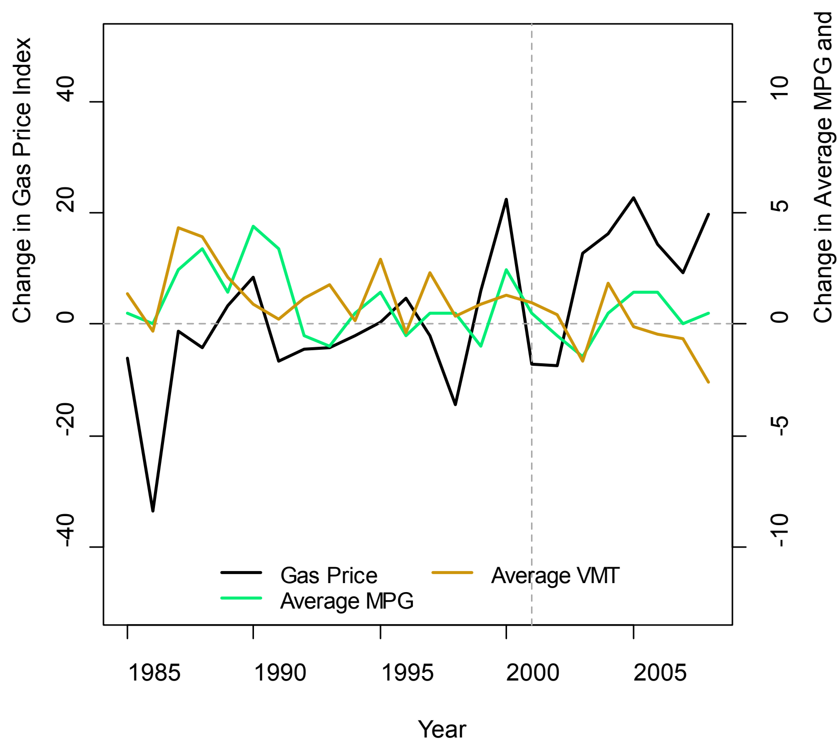
The lower left panel shows that changes in fuel economy and average household VMT were small relative to changes in fuel prices. Moreover, the directions of the fuel economy and VMT trends relative to the fuel price trend imply that the trends may have been independent of one another. One would expect that if fuel price had been a significant motivator of household behavior, fuel economy would have a positive relationship to fuel price (higher prices would lead to higher fuel economy and vice versa) and household VMT would have a negative relationship to fuel price (higher prices would lead to less travel and vice versa).

The fuel economy trend shows the greatest increases occurred between 1984 and 1991 when fuel prices were decreasing the most. After 1991, fuel economy increased very little. Despite the large increase in fuel prices after 2002, there was very little change in fuel economy. The observed trend in fuel economy is probably due to the combination of the effects of CAFE standards and increase in the proportion of light trucks in the vehicle fleet. The CAFE standard for passenger car fuel economy reached a maximum in 1990 and did not change thereafter. In addition, since there was no CAFE requirement for light trucks (pickup trucks, sport utility vehicles, vans) the increasing proportion of light trucks in the fleet would have limited overall improvements in fuel economy.

The relationship of the VMT trend to the fuel price trend during the first portion of the time period is what you would expect if fuel prices significantly affected household VMT. Fuel prices decreased and VMT increased. However the directions of the trends during the latter portion of the time period are not consistent with the expectation that fuel prices influence household VMT. Although fuel prices increased by a large amount from the low point in 1998, household VMT continued to grow up until 2007. Household VMT declined for the first time in 2008, but that arguably could have been caused by the economic recession that started in 2007 and the major financial collapse that occurred near the end of 2008.

The lower right panel shows year to year changes in the indexed values of gas prices, MPG and average VMT. The figure shows that despite year to year changes in gasoline prices of more than 30 percentage points, changes in MPG and average VMT were less than 5 percentage points. Figure 69, which magnifies the MPG and VMT changes by a factor of 4, shows little or no apparent relationship between the direction and timing of changes in gas prices, and that of MPG and VMT.

FIGURE 69. YEAR TO YEAR CHANGES IN GAS PRICES, MPG AND VMT



In conclusion, total household expenditures on transportation have remained fairly constant over the 25 year period from 1984 to 2008. Changes in gasoline prices appear to have had little or no effect on the quantity of gasoline consumed. Changes in price also appear to have had little or no effect on household VMT. The shifting of household expenditures among the different transportation expenditure categories appears to have been responsible for the inelasticity in household gasoline consumption and household VMT with respect to gasoline price.

Although gasoline consumption and VMT have changed little with respect to price over the last 25 years, it would not be wise to assume that this relationship will continue into the future if gasoline prices increase beyond 2008 levels. If the preceding analysis is correct and households do balance out costs within a fixed transportation budget, there will necessarily be adjustments to gasoline consumption if fuel costs rise to high enough levels. At some point, it would no longer be possible to reduce vehicle purchases or other vehicle expenditures in order to avoid reducing gasoline consumption. Vehicles still need to be insured, licensed, maintained and repaired. Vehicle purchases can be put off, but not indefinitely. When a household reaches the point when it longer is possible to shift expenditures to other categories they will have to reduce gasoline consumption. If they cannot increase the fuel economy of the vehicles they drive, they will have to reduce the amount that they drive.

To model the transportation budget it is necessary to estimate the size of the transportation budget. Then it is necessary to estimate the maximum proportion of that budget that can be used for fuel and other variable costs.

First we examine the overall transportation budget and how it varies with household income. Figure 70 shows average transportation expenditures as a percentage of income for the period from 1992 to 2008. This data series starts at 1992 because before that year, all households having incomes above $50,000 were included in one category. Figure 71 shows the same information disaggregated into more income categories at the top end. This data series starts at 2003 because incomes greater than $70,000 were lumped into one category previously.

FIGURE 70. TRANSPORTATION EXPENDITURES AS A PERCENTAGE OF INCOME, 1992 - 2008

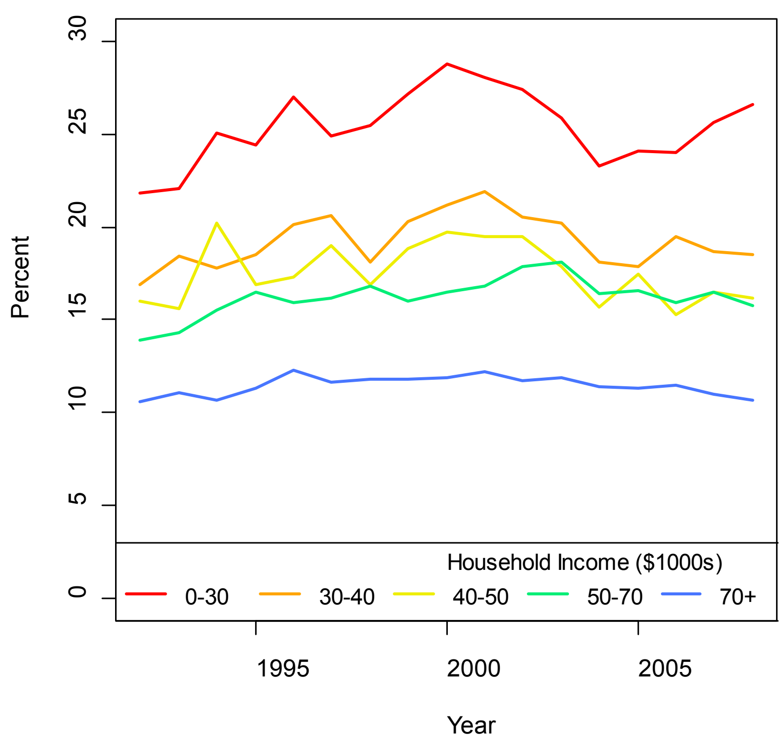
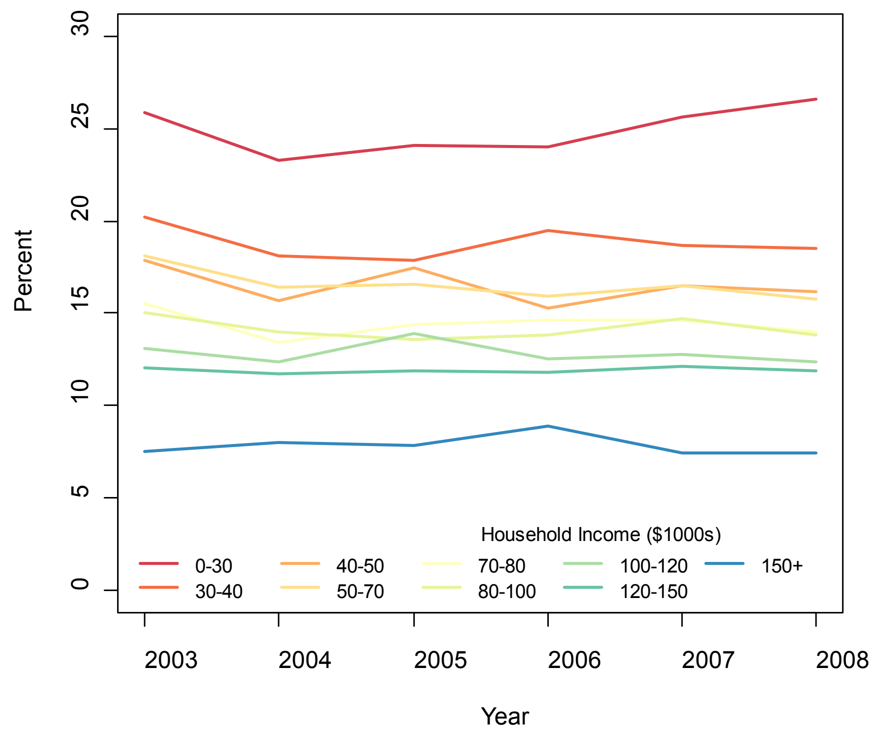


FIGURE 71. TRANSPORTATION EXPENDITURES AS A PERCENTAGE OF INCOME, 2003 - 2008



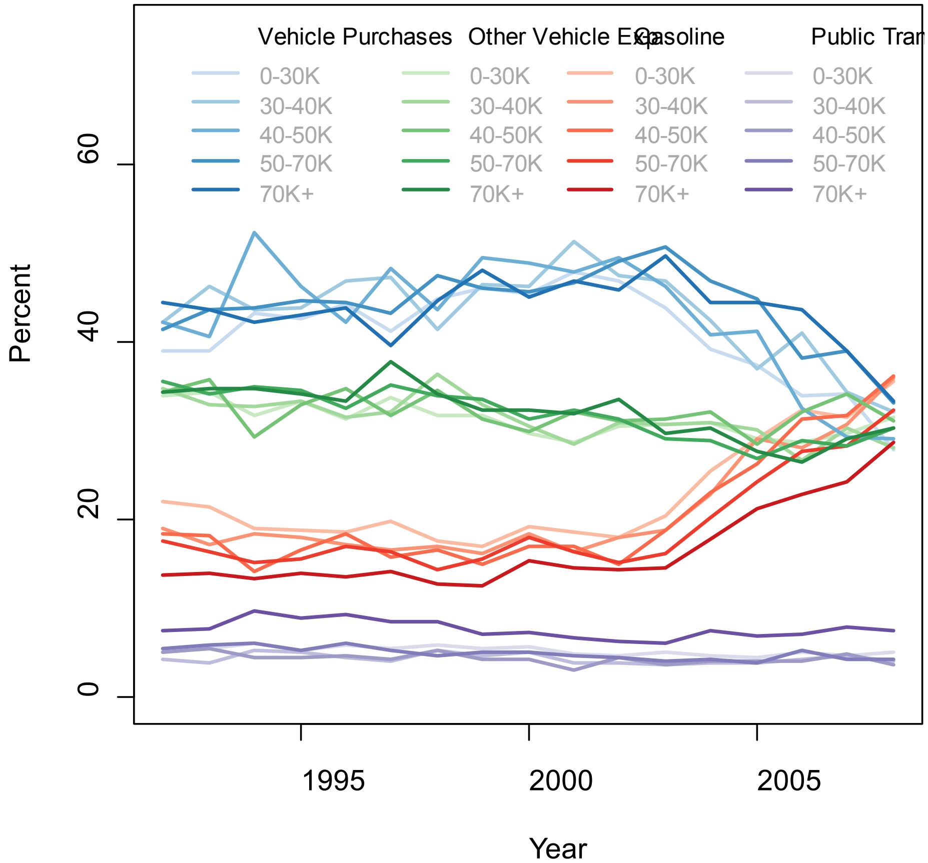
The figures show that the percentage of income consumed by transportation expenditures increases as household incomes decrease. This is to be expected since higher income households save a higher percentage of their income. It is for this reason that higher income household expenditure patterns should not be used in setting the transportation budget. It is better to use households having low enough incomes that they do not save very much since their transportation expenditures will represent a truer maximum.

Caution should be exercised in turning to the lowest income group for guidance. These households report total expenditures that are far in excess of their total incomes. The Bureau of Labor Statistics reports this as due to several factors including non-responsiveness to income questions, underreporting of income, unemployed persons drawing on savings, and self-employed persons experiencing business losses.[32] The household income group earning between $30,000 and $40,000 is the best indicator of an appropriate budget percentage because their incomes and total expenditures are almost equal. The transportation expenditures of these households averaged about 20% of income for the 1992 to 2008 period.

The next question to address is whether the budget used in the model should be the total transportation budget or a proportion of the transportation budget that reflects the maximum amount that might be spent on gasoline and other variable transportation costs. Figure 72 shows the percentage of transportation expenditures spent on different budget categories by households having different incomes.

[32] https://www.bls.gov/cex/csxfaqs.htm#q20

FIGURE 72. COMPONENT TRANSPORTATION EXPENDITURES AS A PERCENTAGE OF TOTAL TRANSPORTATION EXPENDITURES, 2003 - 2008

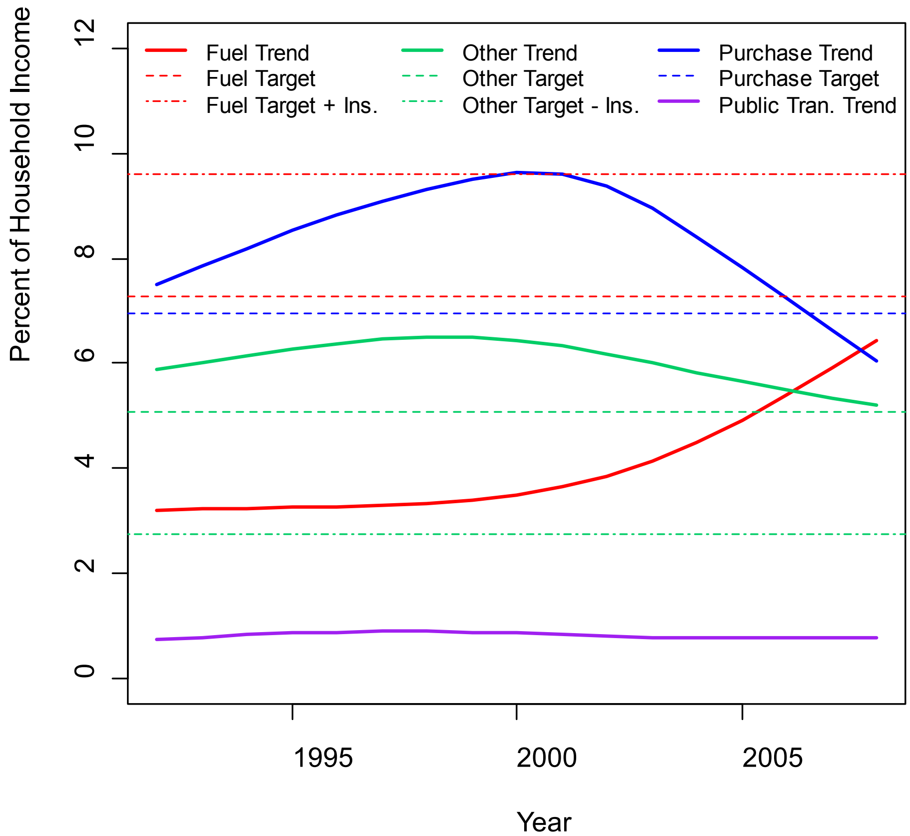


It can be seen that all income groups had very similar proportional splits of transportation expenses between the various categories. There are some noticeable differences though. Lower income households tended to spend a higher percentage on gasoline and a lower percentage on vehicle purchases. The highest income households spend a notably higher percentage on public transportation. This reflects air travel by these households. As before, the 30 to 40 thousand dollar income category is probably the best touch point to use for setting a budget.

Setting a budget for fuel expenditures and other variable costs is a more challenging endeavor because there is no clear indication of what the maximum might be, at least in the CES data. Certainly there must be some limit because vehicles need to be maintained, repaired, insured, licensed and replaced. Figure 72 doesn't indicate any limit. The collapse of the home mortgage market and ensuing economic meltdown in 2008 interrupted the trend so more recent data is of little use.

Since there is no observable budget limit for fuel and other variable costs, estimating this limit is an exercise of judgment and calibration. A proposed target for fuel expenditures was developed by evaluating the trends for the \$30K to \$40K income households and evaluating how the trends for each expenditure category vary with respect to their mean and standard deviation values over the time period. These trends are shown in Figure 73. The trends shown in the figure are smoothed using cubic splines to better show their overall nature. Several prospective limits were evaluated and their sums compared to the overall transportation limit of 20%.

FIGURE 73. ANNUAL TRANSPORTATION EXPENDITURE TRENDS FOR $30K TO $40K INCOME HOUSEHOLDS AND INITIAL TARGETS (SEE TEXT)



It is proposed that a limit for fuel expenditures would be 3 standard deviations above the mean value for the 1992-2008 period. This is approximately 7¼ percent of household income. This is shown by the red dashed line in the figure. This limit could be achieved within the 20% overall budget if vehicle purchase expenses are 1 standard deviation below the mean and other vehicle expenses are 2 standard deviations below the mean (shown by the blue and green dashed lines respectively). This would result in a vehicle purchase expense percentage that is above the 2008 level and close to the 1992 level. The other vehicle expense percentage would be approximately equal to the 2008 level. It is assumed that there would be no change in the public transportation percentage.

Figure 73 also shows what the fuel expenditure target would be if the 2008 percentage of income spent on vehicle insurance is added into the variable cost budget (in order to model pay-as-you-drive insurance). This is shown by the red dashed line at about 10% of income. The corresponding reduction in other vehicle expenses is shown by the lower green dashed line. It is proposed that the final target for gasoline and other variable expenses be 10%.

Form and Testing of the Budget Model

The budget model is very simple. First, a base level of travel is estimated using the average household DVMT model described in the previous section. This model estimates household travel as a function of the household income, number and ages of persons in the household, population density and mixed use character where the household resides, freeway supply and public transit supply. Since 2001 is at the end of a long period of low fuel prices, the model reflects an equilibrium condition between low fuel prices and other factors affecting vehicle travel. It therefore is a good representation of a base level of vehicle travel without budget constraints.

Second a maximum household budget expenditure is calculated based on the assumption about the maximum proportion of household income that may be spent (a default of 10% of household income is assumed[33]). From this budget and the base forecast of vehicle travel, a threshold level for average household cost per mile of travel is calculated. If the cost per mile is less than the threshold level, then the household can continue to travel at the base level. If the cost per mile is greater than the threshold, then the household has to reduce the amount of travel in proportion to the increase in cost above the threshold. Figure 74 shows the shape of the curve for hypothetical households having different incomes. The flat portions of the curves show the potentially inelastic portions to the left of the threshold. The perfectly elastic portions of the curves are to the right of the cost thresholds.

The figure also shows transition curves that may be specified between the inelastic and elastic portions of the curves. The transition curves are calculated using a hyperbolic cosine function that is symmetrical about the average cost threshold. These transition curves are specified by the location of the start of the transition between the base cost per mile and the threshold cost per mile.

Several tests were run on this budget model. The purpose of the first set of tests was to calculate the elasticity of travel demand with respect to fuel price. The metropolitan and non-metropolitan models were applied to the respective household datasets over a range of fuel prices from $1 to $10 dollars per gallon. Fuel price elasticities were then calculated at each dollar increment in the range. Tables 71 and 72 show the results of modeling assuming a full transition. Elasticities increase as prices increase. They decrease as incomes increase. This appears to be reasonable behavior consistent with the budget principle.

The low elasticities at low price increases are consistent with other studies that have found recent price elasticities to be low. To test this further, model runs were done to evaluate how well the model replicates the CES gasoline expenditure trends over recent years.

[33] The model is not hard-coded with this default value. It is possible to input other values.

FIGURE 74. ILLUSTRATION OF BUDGET FUNCTIONS AND TRANSITION CURVES

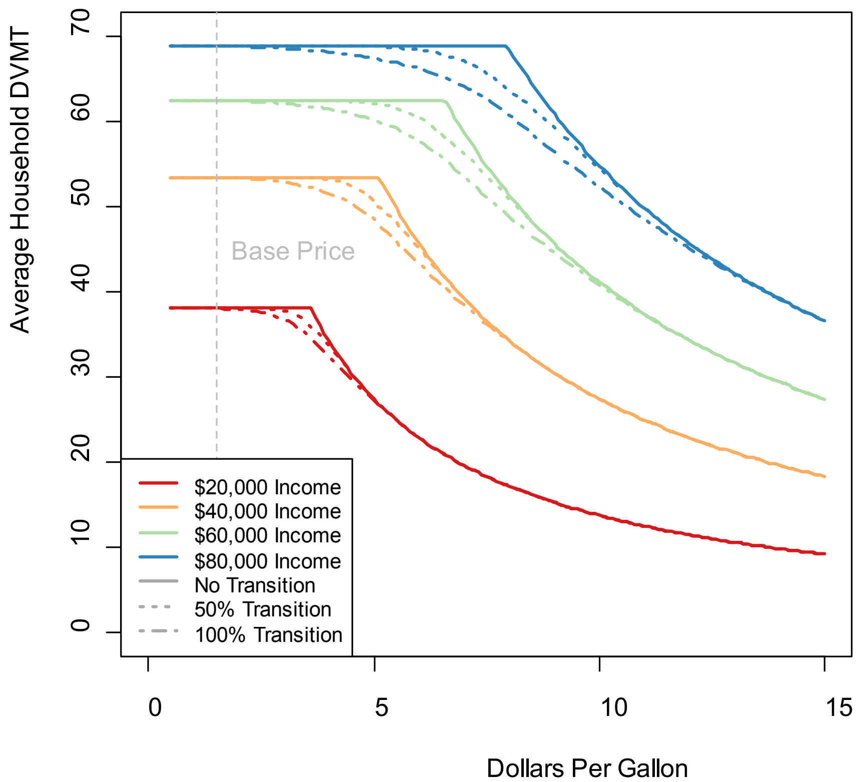


TABLE 71. FUEL PRICE ELASTICITY CALCULATED FROM APPLICATION OF METROPOLITAN DVMT MODEL AND BUDGET MODEL

Income	Fuel Price Range (Dollars per Gallon)								
	$1-$2	**$2-$3**	**$3-$4**	**$4-$5**	**$5-$6**	**$6-$7**	**$7-$8**	**$8-$9**	**$9-$10**
$0-$30K	-0.062	-0.288	-0.495	-0.658	-0.776	-0.854	-0.905	-0.939	-0.960
$30K-$40K	-0.021	-0.150	-0.321	-0.482	-0.619	-0.726	-0.804	-0.860	-0.899
$40K-$50K	-0.016	-0.117	-0.268	-0.428	-0.561	-0.669	-0.754	-0.816	-0.862
$50K-$70K	-0.006	-0.068	-0.198	-0.355	-0.498	-0.619	-0.711	-0.781	-0.834
$70K+	-0.002	-0.032	-0.102	-0.201	-0.315	-0.430	-0.538	-0.629	-0.704

TABLE 72. FUEL PRICE ELASTICITY CALCULATED FROM APPLICATION OF NON-METROPOLITAN DVMT MODEL AND BUDGET MODEL

Income	Fuel Price Range (Dollars per Gallon)								
	$1-$2	$2-$3	$3-$4	$4-$5	$5-$6	$6-$7	$7-$8	$8-$9	$9-$10
$0-$30K	-0.094	-0.418	-0.642	-0.788	-0.880	-0.933	-0.962	-0.979	-0.988
$30K-$40K	-0.027	-0.232	-0.477	-0.658	-0.780	-0.858	-0.909	-0.942	-0.962
$40K-$50K	-0.020	-0.176	-0.396	-0.587	-0.722	-0.812	-0.874	-0.916	-0.945
$50K-$70K	-0.012	-0.106	-0.279	-0.474	-0.631	-0.743	-0.824	-0.881	-0.917
$70K+	-0.009	-0.059	-0.149	-0.271	-0.408	-0.534	-0.640	-0.723	-0.787

Figure 75 shows that the overall average estimate of the proportion of household income spent on gasoline in 2001 produced by applying the model is virtually identical to the CES estimate. Table 73 shows that the model estimates compare favorably to the CES estimates at the income group level as well. The largest discrepancy between the estimates occurs for the lowest income group. This is the least reliable income group target for reasons explained above.

FIGURE 75. COMPARING MODEL TO CES EXPENDITURES IN 2001

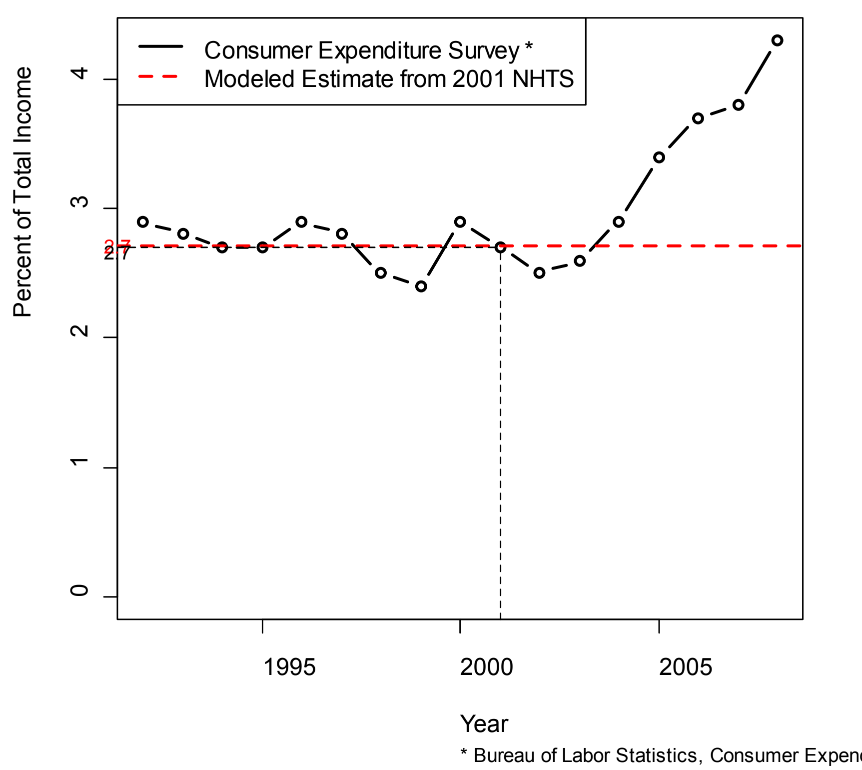


Table 73. Comparison of Model Estimated Household Gasoline Expenditures by Income Group in 2001 with Consumer Expenditure Survey Estimates

	Income Range				
	\$0-\$30K	**\$30-\$40K**	**\$40-\$50K**	**\$50-70K**	**\$70K+**
Model	4.4%	3.3%	3.0%	2.6%	2.0%
CES	5.2%	3.6%	3.3%	2.7%	1.8%
Model/CES	0.85	0.92	0.91	0.96	1.11

A test was also done to compare the model performance with CES expenditure trends from 2001 to 2008 according to the procedure described earlier. The model was run with adjustments to household mileage costs to reflect changes from the 2001 prices. Two sets of model runs were done. In the first set, the transition parameter was set to 0 (i.e. no transition from the inelastic to elastic portions of the curve. In the second set the transition parameter was set to 1 (i.e. households start responding to price increases immediately).

Figures 76 and 77 show the results. The trends are shown in the figure indexed to year 2001 values. This was done because the 2001 starting points of the model and CES estimates are different and because indexing make it easier to visually compare whether rates of growth are the same.

It can be seen from the figures that the model reproduces the CES trend very well. The rates of growth in the percentage of household income spent on gasoline estimated by applying the model are very close to the CES growth rates. The largest deviation occurs in the estimates of the lowest income group which are the least reliable validation targets.

It can also be seen that increasing the transition parameter value to 1 lowers the modeled growth rate but not by much. That is because the price changes that occurred are in the least elastic portion of the function and the departure of the transition curve from the baseline is small in that portion.

The household budget approach solves the problems exhibited by previous models. It matches recent travel trends that have exhibited low fuel price elasticity. It also is sensitive to large increases in prices. Moreover, it does this with a simple and strong conceptual model.

FIGURE 76. COMPARISON OF MODEL AND CES INDEXED TRENDS IN THE PROPORTIONS OF HOUSEHOLD INCOME SPENT ON GASOLINE, 2001 - 2008, TRANSITION PARAMETER = 0

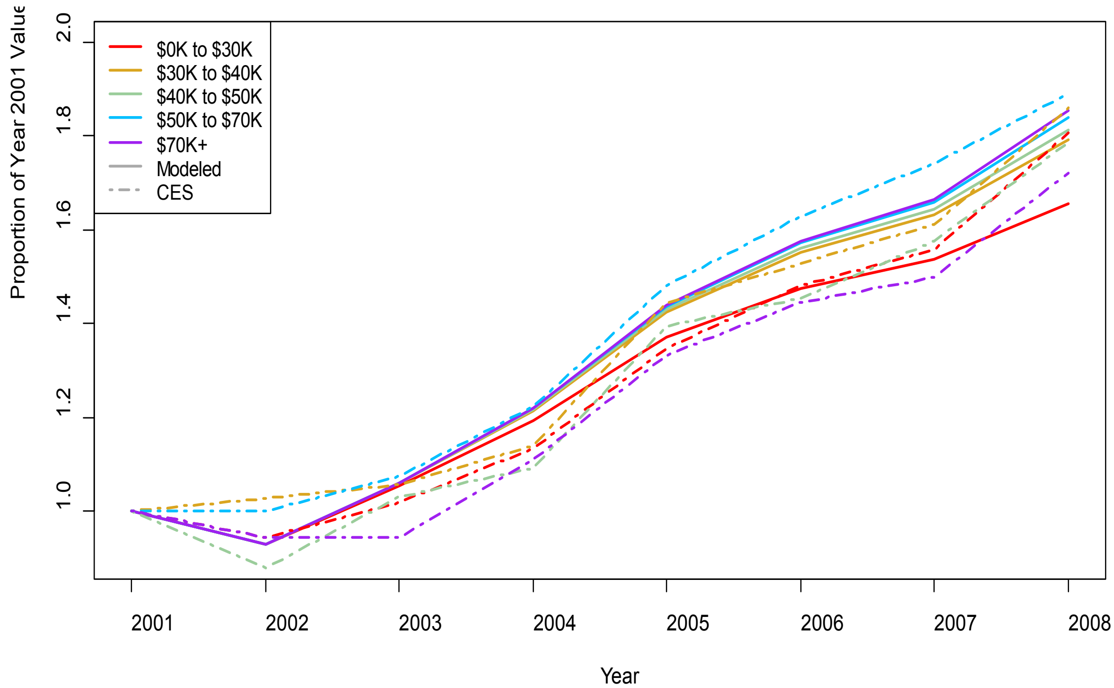
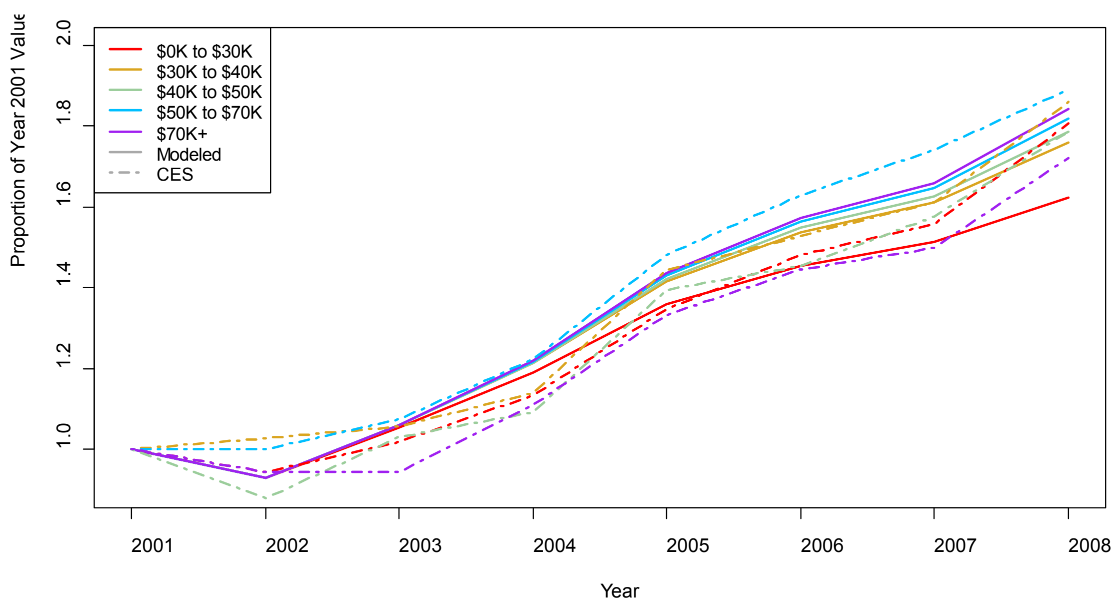


FIGURE 77. COMPARISON OF MODEL AND CES INDEXED TRENDS IN THE PROPORTIONS OF HOUSEHOLD INCOME SPENT ON GASOLINE, 2001 - 2008, TRANSITION PARAMETER = 1



Calculate Travel on Metropolitan Area Roadways and Adjust Fuel Economy to Account for Congestion and Congestion Pricing

Roadway congestion can significantly affect the fuel economy of vehicles powered by internal combustion engines. Idling, acceleration, deceleration and braking all compromise the fuel economy of these vehicles. Hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), and electric vehicles (EV) are less affected by congestion because these vehicles can eliminate idling emissions, recover energy with regenerative braking, and, because of the higher efficiency of electric motors, use less energy during acceleration. The effects of congestion are offset by the effects of vehicle drag (i.e. wind resistance) at higher travel speeds. For the newer vehicles (HEV, PHEV, EV) can result in lower fuel consumption in congested conditions than in uncongested conditions. The GreenSTEP and RSPM models include a congestion model to estimate the effects of these interactions.

The congestion model operates within an overall structure of a networkless aggregate equilibrium model for a metropolitan area. This model splits light-duty vehicle DVMT between freeways and arterials, and between different congestion levels. The proportion of light-duty vehicle travel on local roads (i.e. roads functionally classified as collectors or locals) is set at a fixed value based on traffic volume inventories. Likewise with the proportions of heavy duty vehicle DVMT on freeway, arterial, and local roads. The splits of light-duty vehicle travel between freeways and arterials are sensitive to the relative supplies of freeway and arterial lane-miles, deployment of operations measures (e.g. ramp metering, incident management, coordinated traffic signals, access management), and congestion pricing. Figure 78 illustrates the general structure of the aggregate equilibrium model. Following is a summary description of what the model does.

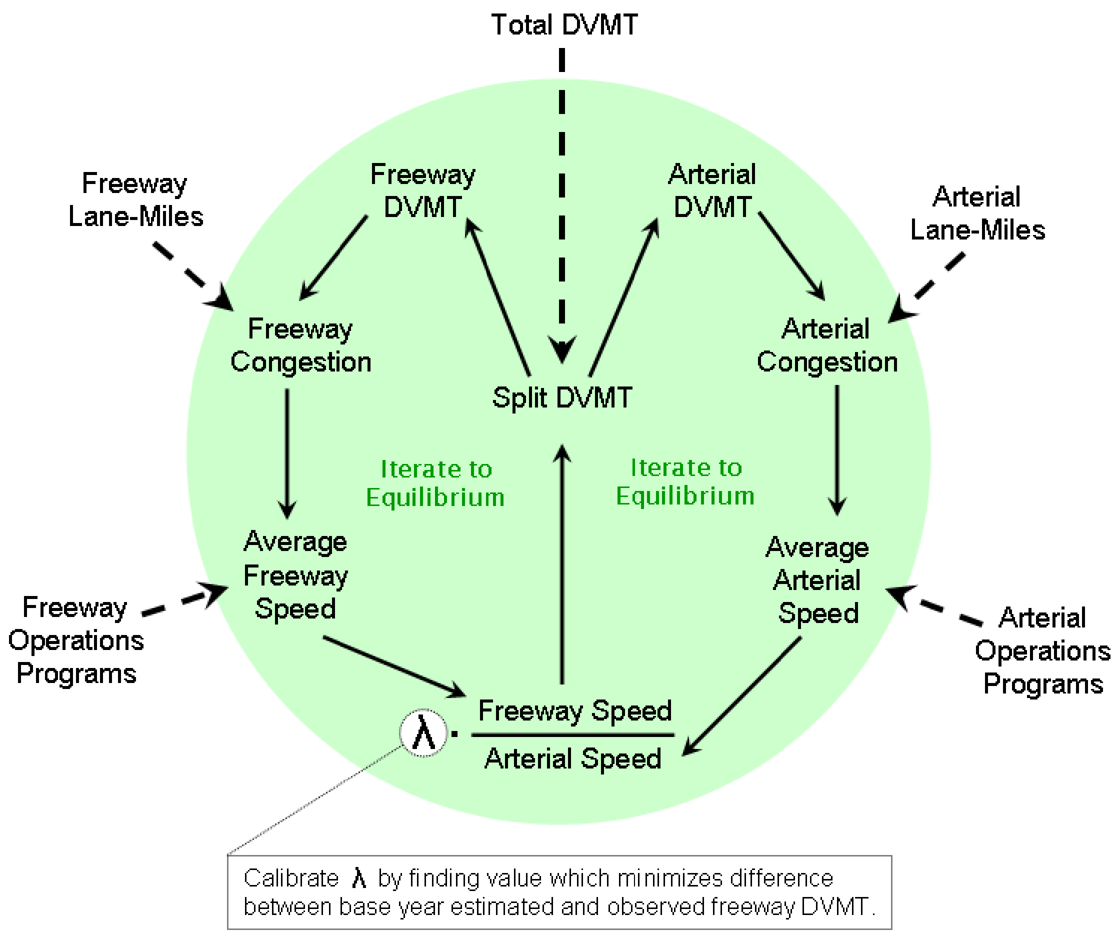
1) Congestion is calculated as a function of DVMT and lane-miles using lookup tables that specify the proportions of DVMT and the proportions of DVHT (daily vehicle hours of travel) in each of 5 congestion categories.

2) Average speed is calculated as a function of congestion level and the type and amount of deployment of traffic operations programs. An average speed is associated with each roadway functional class and congestion level. Those speeds are modified depending on the assumed deployment of traffic operations programs such as ramp metering.

3) A price-adjusted equivalent speed is calculated to account for congestion pricing effects. DVHT by congestion class is calculated from the respective DVMT and speed values. DVHT is converted into a cost equivalent using an assumed value of time. The total cost of congestion pricing by congestion class is calculated from the DVMT and input assumptions on congestion fees per mile by congestion class. Total congestion cost by congestion class is added to the cost equivalent to DVHT. The total overall congestion classes is then summed and divided by the total of all DVMT to produce the price-adjusted equivalent speed.

4) The ratio of average composite speeds determines the split of light-duty vehicle VMT between freeways and arterials. These calculations are repeated until the difference in speeds from one iteration to the next is very small.

FIGURE 78. SCHEMATIC OF AGGREGATE TRAFFIC EQUILIBRIUM MODEL



Only light-duty DVMT on freeways and arterials is allocated in this manner. A fixed percentage of light-duty DVMT is allocated to lower functionally classed roads based on estimates derived from traffic counts. Heavy truck and bus DVMT are also allocated based on fixed input percentages determined by classification counts, and, for buses, by transit agency routing information. It is assumed that heavy truck and bus routing are determined by larger scale routing and delivery needs and are largely insensitive to congestion and prices. Heavy truck and bus DVMT is converted into passenger car equivalents (PCE) for congestion calculations. The PCE for both heavy trucks and buses is 2.5.

Splitting DVMT and DVHT into Congestion Levels

DVMT is split into 5 levels (none, moderate, heavy, severe, extreme), following the approach developed by the Texas Transportation Institute (TTI) for the Urban Mobility Report. In previous versions of the GreenSTEP and RSPM models, linear regression models were used to estimate the proportions of DVMT in all but the moderate congestion category as a function of average traffic loads (ADT/lane). Moderately congested DVMT was calculated as the remainder because the correlation with average traffic loads was very weak. It was subsequently found that the approach of treating the moderately congested category as a remainder resulted in low estimates of the moderately congested proportion of DVMT relative to the proportions estimated for the congestion categories that bracket it (none and heavy). Not only is it that outcome not logical, it also contributed to instability in the model to adjust the DVMT split between freeways and arterials. To produce more sensible distributions a weighted averaging process was used to calculate lookup tables using estimates of DVMT and congestion levels for 90 urban areas prepared by TTI for the 2009 Urban Mobility Report. Average proportions were calculated for each traffic load level (at intervals of 100 ADT per lane) as a weighted average of the values for the 10 urban areas having closest traffic load levels. An urban area's weight was calculated as a direct function of the proportional difference between the subject traffic load level and the urban area's traffic load level. Polynomial splines were fitted to the resulting weighted averages. Figure 79 show the results for the proportions of freeway DVMT by congestion level. The dashed lines in the figure show the results of calculating the weighted averages. The solid lines are the smoothed results. Figure 80 show the corresponding results for arterials. The same method was used to develop lookup tables for splitting vehicle hours of travel (VHT) into congestion bins at different traffic load levels. Figure 81 shows the proportions of DVHT by congestion level for freeways. Figure 82 shows the DVHT proportions by congestion level for arterials.

FIGURE 79. FREEWAY DAILY VEHICLE MILES TRAVELED BY CONGESTION LEVEL FOR DIFFERENT TRAFFIC LOAD LEVELS: WEIGHTED AVERAGES AND SMOOTHED RESULTS

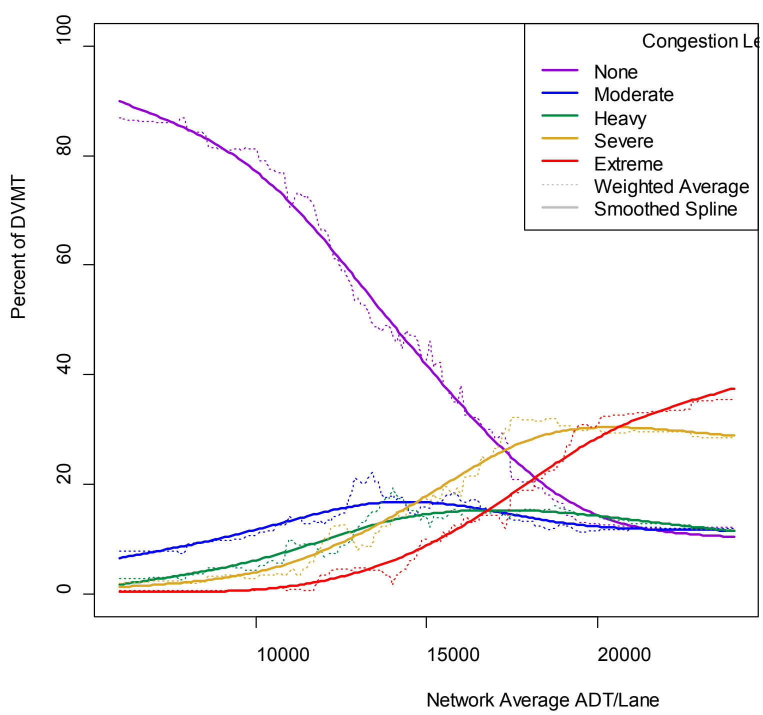


Figure 80. Arterial Daily Vehicle Miles Traveled by Congestion Level for Different Traffic Load Levels: Weighted Averages and Smoothed Results

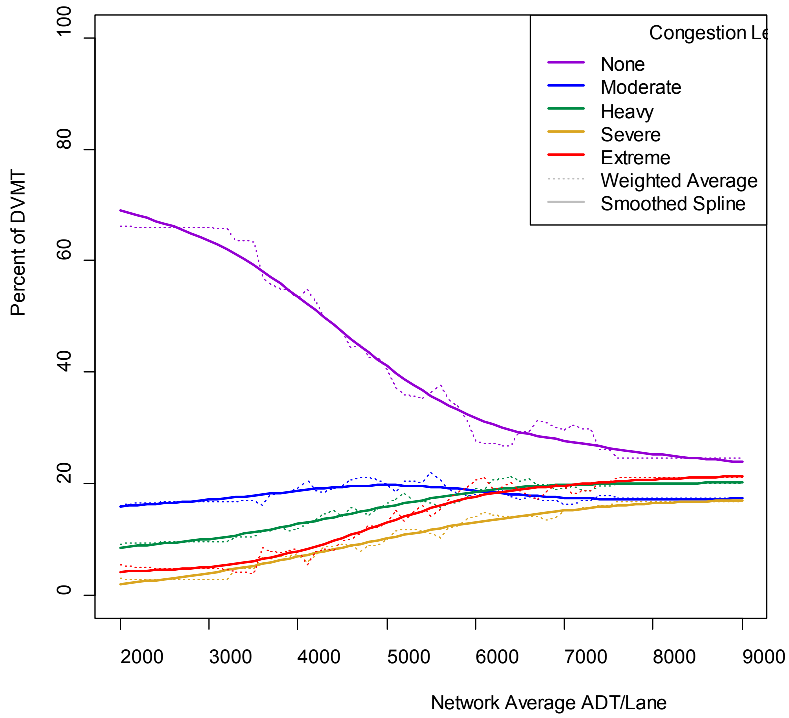


Figure 81. Freeway Daily Vehicle Hours Traveled by Congestion Level for Different Traffic Load Levels: Weighted Averages and Smoothed Results

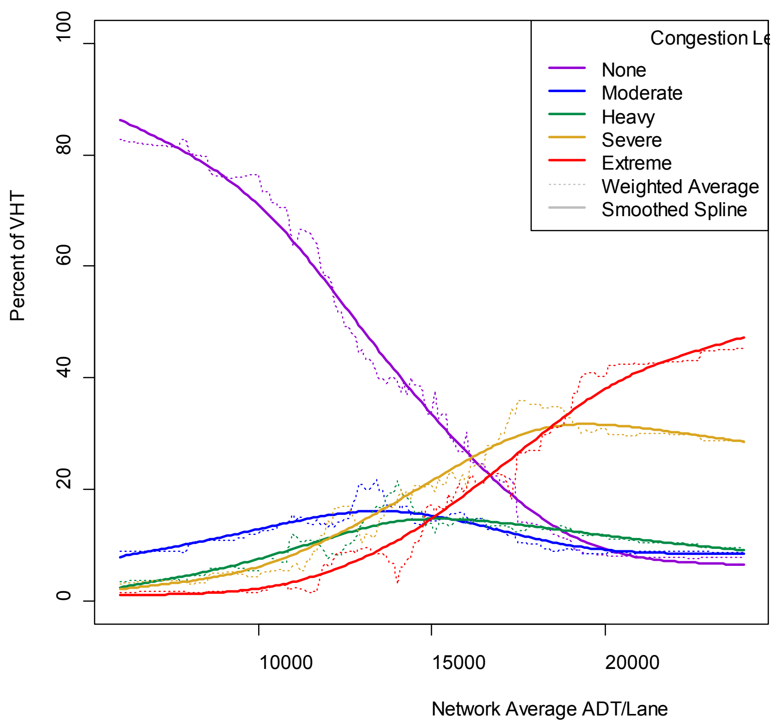
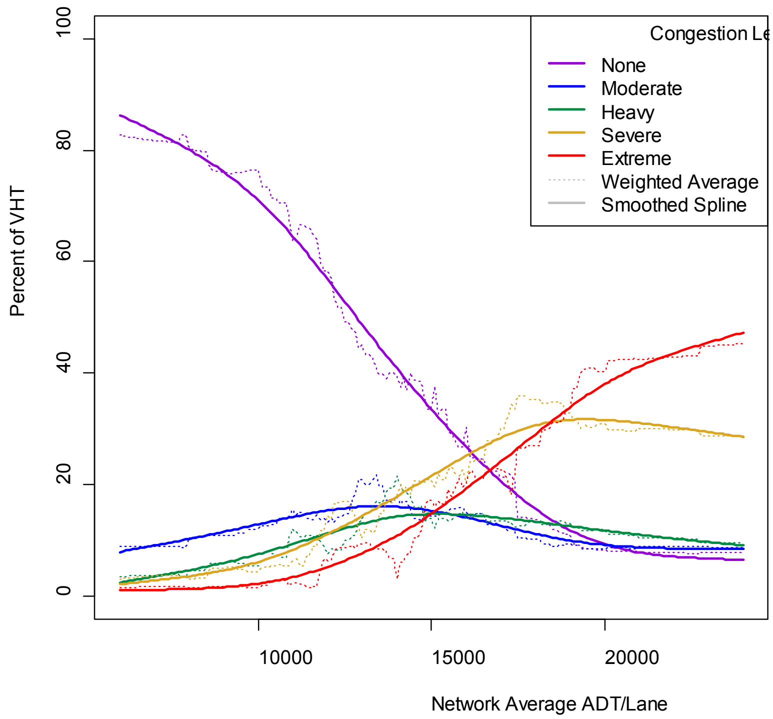


FIGURE 82. ARTERIAL DAILY VEHICLE HOURS TRAVELED BY CONGESTION LEVEL FOR DIFFERENT TRAFFIC LOAD LEVELS: WEIGHTED AVERAGES AND SMOOTHED RESULTS



Estimating Average Speed

Versions 3.0 and 3.5 of the GreenSTEP and RSPM models use a speed model was developed by Alex Bigazzi and Kelly Clifton at Portland State University to enable modeled speeds to be sensitive to operations programs including ramp metering, incident management, traffic signal coordination and access management.[34] This model, like the previous one, uses data on congestion and speeds from the Texas Transportation Institute's (TTI) database for urban areas reported on in the Urban Mobility Report. In addition, it uses research from TTI on the effects of various operations programs on congestion delay. In summary, the model works as follows:

- The process starts with base (no operations programs) congested speeds by congestion level. These are shown in Table 74.
- Amounts of delay due to recurring congestion and to incidents are calculated from the base speeds.
- Four operations programs are considered for their effects on recurring and incident delay. Table 75 shows the maximum percentage reductions in delay with full program deployment. These are the programs for which significant amounts of data are available. The model allows reductions for other programs not listed to be applied as

[34] Alex Bigazzi and Kelly Clifton, "Refining GreenSTEP: Impacts of Vehicle Technologies and ITS/Operational Improvements on Travel Speed and Fuel Consumption Curves. Draft Report on Task 1: Advanced Vehicle Fuel-Speed Curves", June 2011

additional data becomes available or to test the sensitivity of results to potential new programs.

- The delay reduction percentage for an operations program in an individual metropolitan area is calculated based on how extensively the operations program will be deployed relative to the average for metropolitan areas of the same size class in the base year (2007). Table 76 shows the average base year deployment levels by metropolitan area size class in terms of the fraction of maximum delay reduction achieved.
- The calculated delay reduction percentages are applied to the amounts of recurring and incident delay calculated from the base speeds to compute delay which accounts for the effects of operations programs.
- Average speeds by congestion level are calculated from the delay values.
- Average freeway speeds and average arterial speeds are computed as weighted averages using DVMT by congestion level for the weights.

TABLE 74. BASE SPEEDS BY CONGESTION LEVEL

Congestion Level	Overall Average Speed (including effects of incidents)		Average Speed Considering Only Recurring Congestion	
	Freeway	Arterial	Freeway	Arterial
None	60.0	30.0	60.0	30.0
Moderate	50.4	24.9	56.2	29.4
Heavy	44.0	23.5	53.2	28.5
Severe	34.3	22.3	47.4	27.7
Extreme	23.5	20.6	38.8	26.4

TABLE 75. MAXIMUM PERCENTAGE REDUCTION IN DELAY BY OPERATIONS PROGRAM, DELAY TYPE AND CONGESTION LEVEL

Operations Program	Delay Type	Congestion Level				
		None	Moderate	Heavy	Severe	Extreme
Ramp Metering	Fwy. Recurring	0.0	0.0	2.8	5.6	6.3
	Fwy. Incident	0.0	0.0	2.8	5.6	6.3
Incident Management	Fwy. Incident	0.0	13.2	14.9	16.5	18.9
Signal Coordination	Art. Recurring	0.0	10.3	10.1	7.7	5.2
Access Management	Art. Recurring	0.0	0.0	-2.2	-4.5	-6.7
	Art. Incident	0.0	8.0	8.0	9.8	9.8

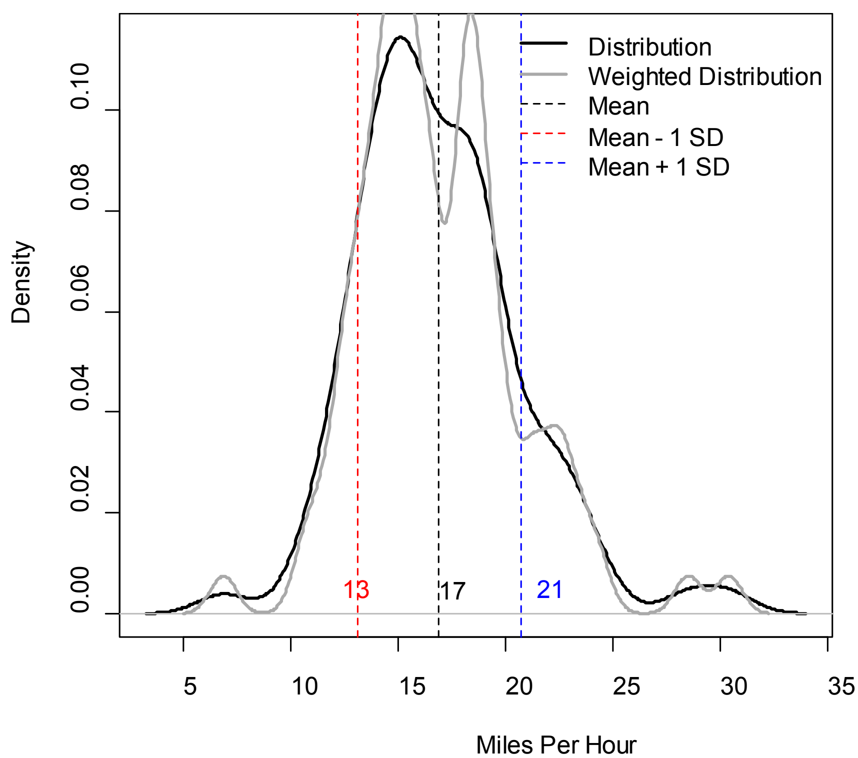
TABLE 76. AVERAGE OPERATIONS PROGRAM DEPLOYMENT LEVELS BY METROPOLITAN AREA IN 2007: FACTION OF MAXIMUM DELAY REDUCTION

Metropolitan Area Size		Operations Program			
Size Class	Population Size (000s)	Freeway Ramp Metering	Incident Management	Signal Coordination	Access Management
Small	< 500	0.00	0.67	0.33	0.28
Medium	500 - 1000	0.03	0.43	0.50	0.42
Large	1000 - 3000	0.43	0.69	0.41	0.49
Very Large	> 3000	0.41	0.78	0.43	0.46

Light-duty vehicle and heavy truck speeds on roads other than freeways and arterials are assumed to be constant at 20 miles per hour.

Bus speeds on freeways are assumed to be the same as for light-duty vehicles and heavy trucks. However, bus speeds on arterials are assumed to be mostly determined by bus schedules. Likewise for bus speeds on other roadways. Bus speed data for the Portland metropolitan roads was analyzed to determine the speeds to use for arterials and other roadways. Figure 83 shows the distribution bus route miles by speed. The average bus speed was assumed to be one standard deviation above the mean (21 MPH) for arterials and one standard deviation below the mean (13 MPH) for other roads.

FIGURE 83. PORTLAND METRO AREA BUS ROUTE SPEEDS



Splitting DVMT into Freeway and Arterial Components

Previous versions (prior to V3.0) of the model used a simple linear regression model to split DVMT into freeway and arterial components as a function of the ratio of the respective number of lane miles. This approach worked reasonably well for existing conditions, but testing revealed that the model would overestimate the amount of expected shift in DVMT from freeways to arterials or vice versa when the balance of lane miles changes. Moreover, the model was not sensitive to the effects of operations programs that affect average travel speeds without changing the number of lane miles.

The observed problems with the previous model occurred because lane-miles is a proxy for the real attribute influencing the relative amounts of travel on freeways and arterials; average speed (or travel time). People decide which routes to use in large part based on how much time it will take to get to their destinations via those routes. While average freeway and arterial speeds are affected by the respective numbers of lane-miles, they are also affected by the respective amounts of travel and programs that affect how efficiently those lane-miles may be used (e.g. operations programs). Lane-miles are only one factor which affects how DVMT and speeds are balanced in an urban roadway system.

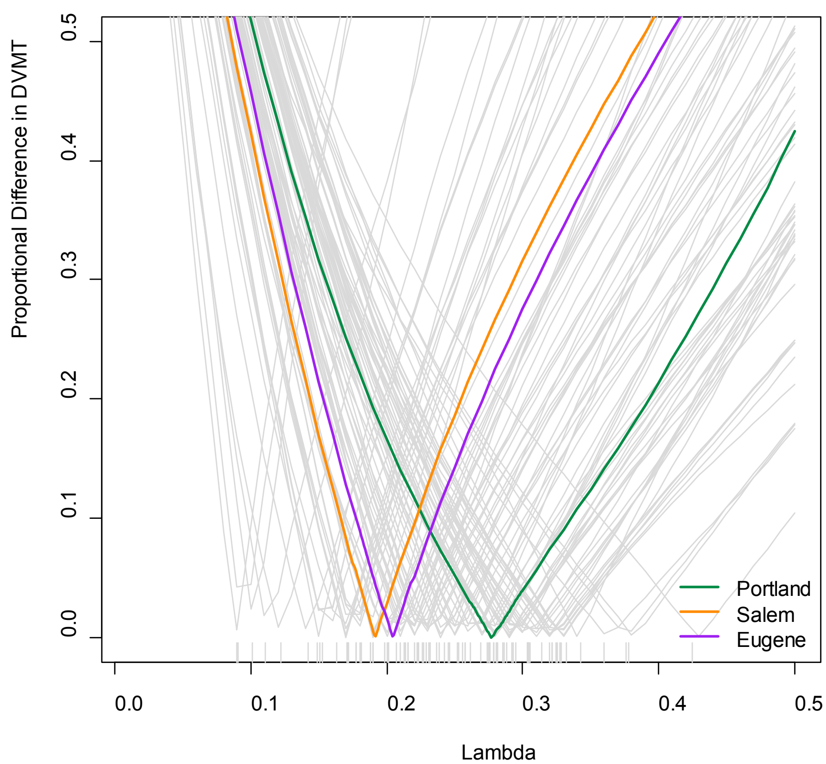
The challenge for modeling the urban roadway system correctly is that DVMT and average speeds affect each other. For example, if freeway speeds are increased by some program or action, some drivers will find it to their advantage to switch some of their travel to freeways from arterials. This will increase the amount of freeway DVMT and counteract to some degree the freeway speed advantage. Because of this interrelationship between speed and DVMT, a simple linear model can't be used to split DVMT into freeway and arterial components. What is needed instead is a model which solves the DVMT split by finding the point where freeway and arterial DVMT and speeds operate in equilibrium.

The green circle in the figure shows portions of the model that are repeated until an equilibrium condition is found (i.e. where the DVMT split changes very little with each additional iteration). Outside of the circle are exogenous factors that influence the internal conditions of the model. The model procedure starts with an initial splitting of total freeway and arterial DVMT is into the respective components using a lane-mile based linear model. Once that has been done, the respective DVMT's are split into congestion levels using the lookup tables described above. Then, average speeds are computed using the methodology described in the previous section. The ratio of average freeway speeds to average arterial speeds is multiplied by a factor (shown as λ in the figure) to calculate the freeway proportion of total freeway and arterial DVMT. The cycle repeats, with the exception of the initial step to split DVMT into freeway and arterial components based on lane-miles, until an equilibrium state is achieved.

The λ value was estimated using the TTI urban dataset by running the model successively for values between 0 and 1 in increments of 0.01 and finding the value for each metropolitan area which minimized the difference between the observed and estimated freeway DVMT. For the Oregon metropolitan areas included in the dataset (Portland, Salem, Eugene), the λ values were determined more precisely by testing at smaller increments. Figure 84 shows that:

1. The model does reach equilibrium over a range of λ values;
2. A value exists for each metropolitan area where the estimated freeway DVMT is equal to the observed value; and
3. That the values are in the range between 0.1 and 0.4.
4. The Portland, Eugene and Salem metropolitan areas are near the center of the range with values of 0.277, 0.204 and 0.192 respectively.

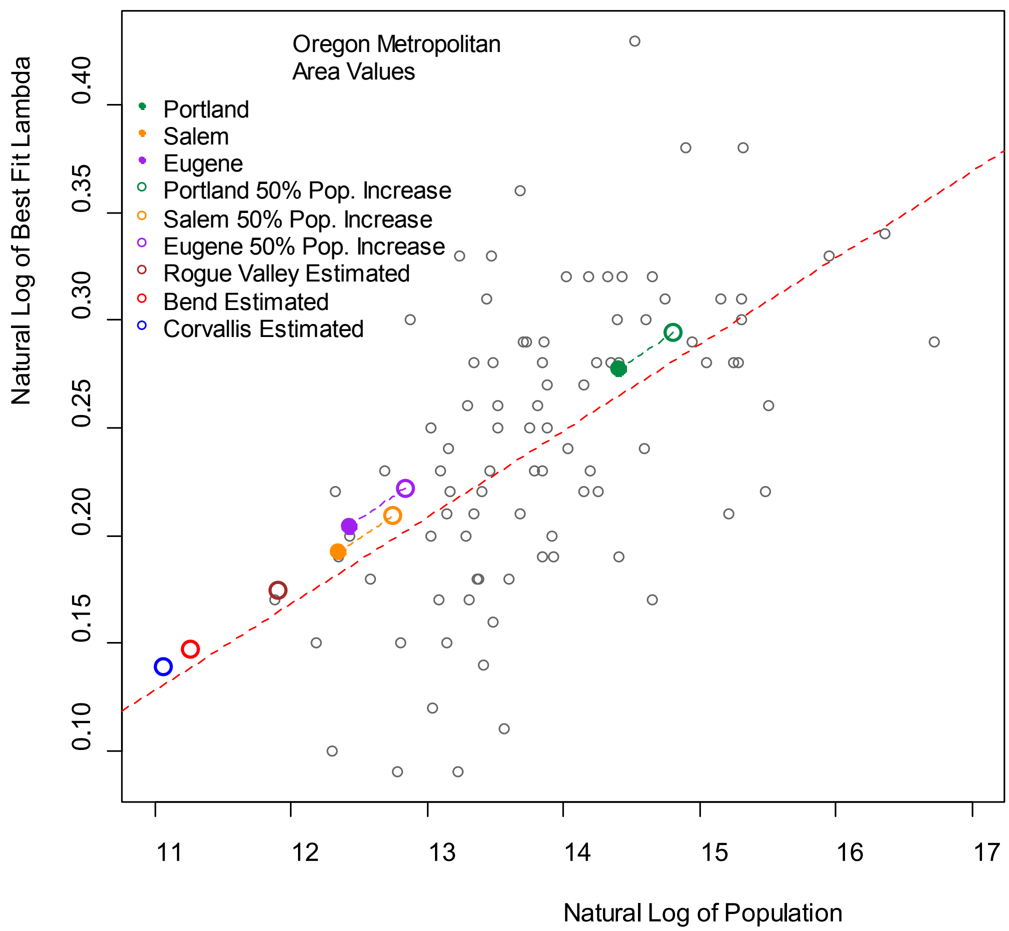
FIGURE 84. ERROR IN FREEWAY DVMT ESTIMATION FOR 90 METROPOLITAN AREAS IN RELATION TO VALUE OF LAMBDA



The variation in λ values between urban areas probably reflects a number of differences between urban areas. For example, the density of freeway interchanges is likely to affect the proportion travel occurring on freeways. Since the only data available at the time was the respective numbers of freeway and arterial lane-miles in relation to population, the model couldn't be sensitive to these other factors.

Population though, is a factor that the model should address. It can be seen from Figure 84 that the smaller metropolitan areas, Salem and Eugene, metropolitan areas have lower λ values than the Portland metropolitan area and that Salem, the smaller of the two, has the lowest value. This suggests that there may be a relationship between λ and population that should be accounted for. This relationship is shown in Figure 85. Although differences in population only explain a minority of the variation in λ values (r-squared = 0.31), the relationship between population and λ is very strong (t value = 6.345). This relationship is used in the new model to adjust λ values as urban areas grow in population. It is also used to estimate λ values for the smaller metropolitan areas that are not included in the TTI database. Figure 85 shows the estimated values for the smaller metropolitan areas in Oregon. It also shows how the values would change for the 3 larger Oregon metropolitan areas if their populations grow by 50%.

FIGURE 85. RELATIONSHIP OF LAMBDA VALUES TO METROPOLITAN AREA POPULATION



This procedure only affects the split of light vehicle travel between freeways and arterials. It is assumed that the splits of truck and bus DVMT reflect larger scale routing and delivery functions that are largely insensitive to relative freeway and arterial speeds.

Modeling Congestion Pricing

Congestion pricing is very challenging to model because of the variety of responses that might occur: drivers may change the routes that they drive, the times that they drive, and/or the amounts that they drive. The congestion model described in this section addresses at a general level the first two of these responses (which routes and when). The third response (amount of driving) is dealt with in the household travel budget model for GreenSTEP.

The congestion pricing model is implemented within the framework of the equilibrium travel model described above and based on the fundamental theoretical principle that time has a money equivalent that can be estimated. Given that principle, vehicle hours can be converted into cost equivalents and likewise congestion pricing can be converted into time equivalents. This forms the basis for how congestion pricing is brought into the equilibrium travel model to influence both the split of DVMT between freeways and arterials and the split of DVMT into congestion categories.

In the model, congestion pricing affects the DVMT between freeways and arterials by adjusting the speed ratio to reflect prices as follows (calculated separately for freeways and arterials):

1. VHT by congestion level is calculated by dividing the DVMT by congestion level by the average speed by congestion level.
2. Equivalent cost of the VHT by congestion level is calculated by multiplying the VHT by the average estimated value of time.
3. The cost of congestion pricing by congestion level is calculated by multiplying the specified price per VMT for each congestion category by the DVMT in each congestion category.
4. The total cost of travel by congestion category is calculated by adding the time equivalent cost to the congesting pricing cost.
5. The equivalent VHT by congestion category is calculated by dividing the total cost by congestion category by the average value of time.
6. The total VHT equivalent value is divided into the total DVMT to calculate an equivalent average speed which is used in the speed ratio. The equivalent average speed by congestion bin is also calculated for use in the procedure described below by dividing the equivalent VHT by congestion bin into DVMT by congestion bin.

It should be noted that this congestion pricing procedure only affects the distribution of light vehicle traffic between freeways and arterials. It is assumed that truck and bus travel is determined by larger scale routing and delivery needs that will be largely insensitive to prices.

The model also addresses the effects that congestion pricing would have on the travel occurring at different times and/or portions of the freeway and arterials systems by adjusting the calculation of DVMT by congestion bin. The procedure is as follows:

1. Total DVMT (freeway or arterial) is converted into total equivalent VHT using the respective equivalent average speed described above.

2. Total equivalent VHT is split into congestion bins using the corresponding traffic load value for the facility (freeway or arterial).

3. Equivalent DVMT by congestion bin is calculated by multiplying the equivalent VHT by congestion bin by the equivalent speed by congestion bin.

4. DVMT proportions by congestion bin are calculated from the equivalent DVMT by congestion bin.

The congestion model calculates the average cost of congestion pricing per light vehicle VMT by summing the total congestion cost for freeways and arterials and dividing by the total freeway and arterial light vehicle DVMT. The resulting value is used in the module that adjusts household DVMT as a function of vehicle travel costs and household budgets. This is how congestion pricing affects the amount of vehicle travel.

Modeling the Effects of Speed on Fuel Economy

The Version 3.5 (and Version 3.0) GreenSTEP and RSPM models incorporate a new vehicle efficiency model developed for ODOT by Alex Bigazzi and Kelly Clifton at Portland State University[35]. This model calculates the effect of changes in speeds on vehicle efficiency relative to the fleet average efficiency (e.g. fuel economy). The previous model used fuel speed curves (FSC) from average values reported in the Transportation Energy Databook and values used in the MOVES model. Those reported values are for older internal combustion engine (ICE) powertrain vehicles. That posed a problem for modeling future scenarios which assume substantial percentages of advanced powertrain vehicles such as hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), and all electric vehicles (EV). To fix this, Bigazzi and Clifton used EPA's PERE model to evaluate 177 light duty vehicles and trucks having various powertrain and other characteristics that affect the vehicle efficiency with respect to speed. The results of the research show that advanced powertrain vehicles operate more efficiently in congestion than ICE vehicles.

The new model includes high efficiency and low efficiency prototypes for each type of vehicle powertrain. A new input parameter allows the model user to specify the relative congestion efficiency of the vehicle on a scale from 0 to 1. This value is used to produce a weighted average FSC from the corresponding low efficiency and high efficiency prototypes.

The new model also corrects a double counting problem with the previous model. In the previous model, efficiency adjustments were normalized relative to free-flow travel speeds. This

[35] Alex Bigazzi and Kelly Clifton, "Refining GreenSTEP: Impacts of Vehicle Technologies and ITS/Operational Improvements on Travel Speed and Fuel Consumption Curves. Draft Report on Task 2: Incorporation of Operations and ITS Improvements.", June 2011.

approach did not account for the fact that average fuel economy is reported for a typical driving speed that is lower than the free-flow travel speed. The new model normalizes FSCs consistent with the EPA basis for computing average fuel economy.

Finally, the model was modified to account for the effect of speed smoothing, resulting from variable speed signing, other traffic controls, or eco-driving. This portion of the model adjusts FSCs relative to the theoretical maximum efficiency constant speed condition. The researchers determined that the maximum benefit that could be expected would be half of the theoretical maximum benefit. The model calculates the average efficiency adjustments due to speed smoothing based on input assumptions regarding the percentage of drivers that follow eco-driving practices and the percentage of DVMT that is subject to speed smoothing traffic management actions.

Calculate Commercial Service Vehicle Emissions, Costs, and Revenues

Commercial service vehicles are light-duty vehicles used for deliveries, service calls, and other business purposes. Prior to Version 3, travel and emissions by these vehicles were not explicitly modeled. Instead, all light-duty vehicle travel was attributed to households. This was changed in Version 3 because commercial service vehicles, given that they are often managed as fleets, offer some different opportunities for managing emissions. For example, because using compressed natural gas (CNG) as a vehicle fuel requires specialized fueling equipment, it is easier for a commercial vehicle fleet operator than a household to operate CNG powered vehicles.

Versions 3 and 3.5 enable the potential for reducing GHG emissions through commercial fleet-oriented actions to be assessed by allowing the user to specify the following characteristics for commercial service vehicles differently than for household vehicles:

- Vehicle age distribution by vehicle type;
- Light truck proportions;
- Fuel type proportions; and,
- Powertrain (e.g. ICE, HEV, PHEV, EV) proportions.

The model inputs don’t distinguish commercial service vehicles from household vehicles with respect to vehicle characteristics by vehicle type, powertrain type and model year (e.g. auto MPG by model year, PHEV battery range, etc.).

Commercial service vehicles and commercial service vehicle travel, unlike household vehicles and vehicle travel, are not simulated. Instead, the DVMT of commercial service vehicles is estimated at the county level for GreenSTEP models and at the division level for RSPM models. Then fractions of that travel are allocated to different vehicle types, powertrains, ages, and fuel types based in the scenario inputs.

In the design of both versions 3 and 3.5, the demand for commercial service vehicle travel is assumed to be caused by household demand. In other words, it is household demand for products and services that causes commercial service vehicle travel to exist. However, the two versions calculate commercial service vehicle travel demand differently. Version 3 calculates commercial service vehicle travel as a fixed proportion of the household vehicle travel. That proportion is calculated by comparing the total estimates of light-duty vehicle travel for the state using HPMS data with GreenSTEP-modeled light-duty vehicle travel. For Oregon, using the Version 3.5 of the model, the difference is equal to about 9 percent of the household light-duty vehicle travel.

Version 3.5 does not use the fixed proportion approach used by version 3. Instead, it calculates commercial service vehicle travel in relation to total household income. This is a more accurate representation of the dynamics that cause commercial service vehicle travel to exist. For example, with version 3 which directly relate commercial service vehicle travel to household travel, travel demand management (TDM) programs that reduce household vehicle travel, also reduce commercial service vehicle travel. This is not realistic because household-oriented TDM programs have no effect on commercial service vehicle travel, and households may in fact substitute commercial service vehicle travel for household travel (e.g. ordering a product on line instead of driving to a store to buy it).

To calculate commercial service vehicle travel, version 3.5 calculates a ratio of commercial service vehicle DVMT to total household income for the base year. This ratio is then used in other model years to calculate commercial service vehicle DVMT based on total household income. Commercial service vehicle DVMT in the base year is computed from household DVMT in the base year using the fixed proportion (e.g. 9 percent) that is estimated as described above.

Calculate VMT Tax Needed to Pay for Assumed Road System

GreenSTEP and RSPM versions 3 and 3.5 allow model users to calculate and apply road use taxes sufficient to pay for the assumed road system. This capability was added to the models to facilitate fair comparisons of scenarios that specify different strategies for reducing GHG emissions. This is particularly important because one of the important performance measures produced by the models and used to compare scenarios is household vehicle expenses. Following are some examples of how comparisons could be distorted if the costs to build and operate the roadway system are not passed back to households. For example, a strategy oriented towards reducing emissions by building roadways and reducing congestion will underestimate household vehicle costs if the costs are not passed back to the road users. It will also overestimate household travel if households don’t pay those costs. This capability also enables users to estimate how much vehicle-mile taxes would need to be in order to fund the road system as vehicle fuel economy increases in the future and as a higher proportion of vehicles are powered by electricity.

The models calculate the costs to maintain and operate the roadway system differently than the costs to expand the system. The costs to maintain and operate the roadway system are calculated using inputs that are specified on a per vehicle mile basis for light-duty vehicles. There are three costs that are specified in this way: base modernization (i.e. modernization improvements that don't involve major capacity expansions such as intersection channelization and minor roadway realignment), preservation/operations/maintenance (e.g. roadway resurfacing, traffic signals, drainage), and other costs (e.g. administration and planning). The unit cost input needs to reflect that portion of the cost that is attributable to light duty vehicles. The costs to expand the system are calculated on a lane-mile basis (i.e. cost to add a freeway lane-mile and cost to add an arterial lane-mile). The portion of the road system expansion costs attributable to light-duty vehicle travel is calculated as the ratio of light-duty vehicle DVMT to total passenger-car equivalent DVMT. The costs of roadway expansions are annualized by assuming that specified lane-mile additions over a period are added at the assumed population growth rate.

The total road user taxes collected from light-duty vehicle users are calculated by multiplying the gallons of fuel consumed by the specified fuel tax rate and the vehicle miles traveled by the mileage tax rate (specified and computed by the model).

The difference between the total roadway costs attributable to light-duty vehicle travel and the total road user taxes collected from light-duty vehicle users is then divided by the total light-duty vehicle VMT to calculate the added mileage tax needed to fund the roadway system specified in the scenario. This is done on a statewide basis for the GreenSTEP model and on a metropolitan area basis for the RSPM.

Adjust Fuel Economy to Account for Eco-driving and Low Rolling Resistance Tires

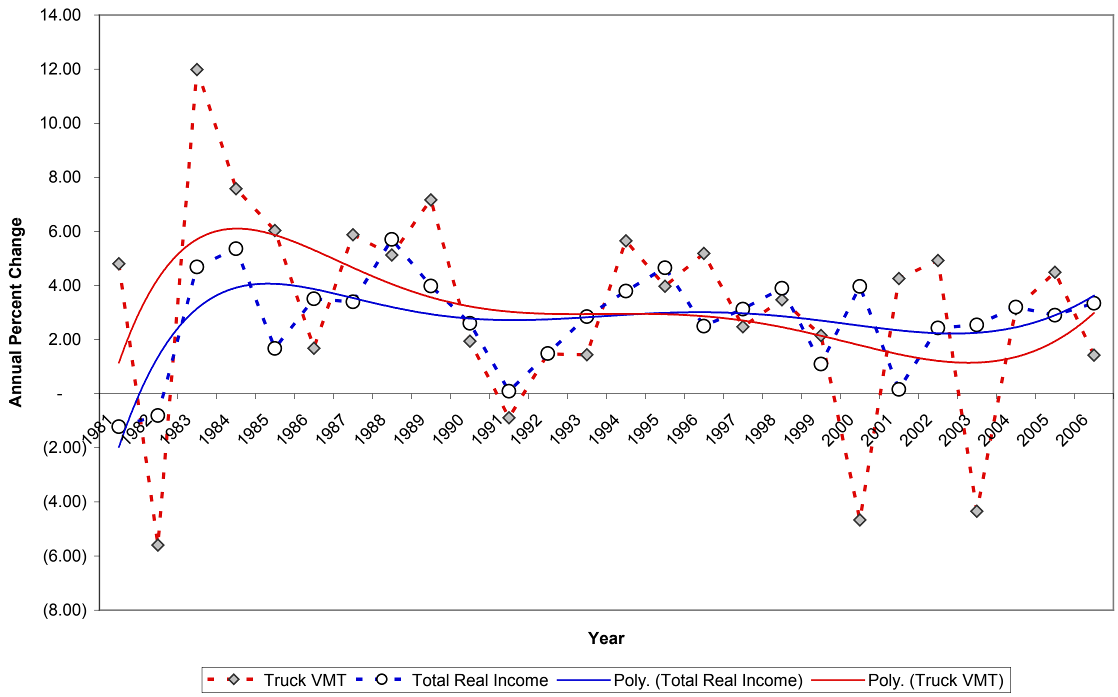
In versions of the models prior to version 3, the effect of eco-driving on household vehicle fuel economy was calculated as a fixed proportional improvement. This was changed in version 3 to be a more sophisticated calculation that relates eco-driving to speed smoothing. This is described in the section "*Modeling the Effects of Speed on Fuel Economy*" above.

The effects of low rolling resistance tires are modeled as a fixed percentage improvement for households that are assigned to the use of these tires. The model assumes that using these tires increases average fuel economy by one percent.

Calculate Heavy Truck Travel, Fuel Consumption and Greenhouse Gas Emissions Adjusted for Congestion

Heavy truck VMT is calculated on a statewide basis as a function of the base year estimate of heavy truck VMT and the growth in the total statewide income. The trend has generally followed the statewide income trend over the past 15+ years, although year-to-year changes in heavy truck VMT have been more volatile than changes in total statewide income. Figure 86 shows that heavy truck VMT grew at a faster rate than total income until about 1995 and at a slower rate afterwards. As a default, the model grows heavy truck VMT at the rate of total statewide income, but the user can apply a factor to change the relative rate of heavy truck growth.

FIGURE 86. ANNUAL GROWTH RATES OF TRUCK VMT AND TOTAL STATEWIDE INCOME



The forecast of heavy truck VMT is straightforward. Future total statewide income is calculated from the sum of modeled household income. Then the percentage change in total statewide income from the base year is calculated. The base year heavy truck VMT is multiplied by this change and any relative change factor the user may have supplied.

Heavy truck VMT is attributed to metropolitan areas to calculate metropolitan congestion. This is done by applying fixed proportions that were calculated for the base year (2005) using data from state highway vehicle counts, the Federal Highway Cost Allocation Study[36], and HPMS data for Oregon. Traffic count data for state highways was used to allocate truck VMT between urbanized and non-urbanized areas; 28% and 72% respectively. The Federal Highway Cost Allocation Study was used to calculate the average proportion of truck VMT by urban area functional class (Table 77). The amount of the VMT in each urbanized area that is truck VMT was calculated by applying the proportions calculated in Table 77 to the HPMS estimates of VMT by functional class calculated for each urbanized area. The proportions total state truck VMT in each urbanized area was then calculated from those results. These are shown in Table 78.

[36] Table II-6, 1997 Federal Highway Cost Allocation Study Final Report, Chapter II,

https://www.fhwa.dot.gov/policy/hcas/final/two.cfm

TABLE 77. HEAVY TRUCK VMT PROPORTIONS BY URBAN ROADWAY FUNCTIONAL CLASS

Functional Class	Heavy Truck Proportion
Principal Arterial – Interstate	8.3%
Principal Arterial – Other Freeway or Expressway	5.6%
Principal Arterial – Other	5.4%
Minor Arterial	4.2%
Collector	3.8%
Local	3.6%

TABLE 78. HEAVY TRUCK VMT PROPORTIONS BY METROPOLITAN AREA

Metropolitan Area	Proportion of Heavy Truck VMT
Portland Metro	19.1%
Salem-Keizer	2.8%
Eugene-Springfield	2.7%
Rogue Valley	1.9%
Bend	0.8%
Corvallis	0.05%

Average fleet fuel economy for heavy trucks is calculated similar to how it is calculated for light vehicles. Heavy truck fuel economy by model year is an input to the model. Different assumptions on future improvements to fuel economy can be modeled by varying these inputs. Heavy trucks are assigned to age bins based on a reference truck age distribution and input assumption for adjusting the 95th percentile truck age. The age proportions by model year are used with the fuel economy inputs by model year to compute an overall fleet average fuel economy.

Calculate Metropolitan Area Bus and Passenger Rail Travel, Fuel Consumption and Greenhouse Gas Emissions Adjusted for Congestion

Annual transit revenue miles are calculated for each metropolitan area to provide inputs to the household vehicle ownership and travel models. It is a straightforward process to compute total bus and passenger rail vehicle miles travel by multiplying the revenue miles by a factor that accounts for non-revenue service travel. A statewide average of 1.15 is used.

Fleet average bus fuel economy and rail energy efficiency are computed in the same fashion as heavy truck fuel economy with some differences. Bus fuel types are specified at the metropolitan area level in the GreenSTEP model. This is done because there can be substantial differences in the fuel mix used by different metropolitan area transit districts. For example, in Oregon the Rogue Valley and Salem-Keizer transit districts use a much higher percentage of CNG than other transit districts in the state. Bus and train age distributions are specified at the statewide level in the GreenSTEP model (the RSPM specifies them at the metropolitan level of course). Fuel economy of buses is specified in the same way as for trucks, and as with trucks, it is not possible to explicitly account for advanced powertrains such as hybrid electric vehicles other than by adjusting the scenario assumed fuel economy to account for those vehicles. As with heavy trucks, fuel economy is specified by model year. Although advanced powertrain vehicles are not explicitly modeled, the models do explicitly model electrically powered passenger rail and buses. In version 3.5, the user can specify the proportion of bus DVMT that is powered by electricity by metropolitan area. It is assumed that all rail travel is powered by electricity. As with electric vehicles, the emissions from electrically powered buses and trains are calculated based on the amount of electricity consumed and the emissions rates for producing and transporting electricity to the metropolitan area.

Household Travel Model Sensitivity Testing

A number of tests were performed to evaluate the sensitivity of the household travel models to changes in various inputs.

Most of the sensitivity tests measure the amount of change in household DVMT that occurs with changes to each of the following factors: household income, fuel price, population density, freeway supply, public transit supply, and fuel economy. A test of sensitivity of fuel consumption to vehicle fuel economy was also run to measure the size of the rebound effect. This is the reduction in the impact of MPG improvements on fuel consumption due to the effect of reduced per mile fuel cost on household DVMT.

The tests were performed using the NHTS household survey dataset used for model estimation. The model sensitivity to each variable is reported as the ratio between the percentage change in model outputs (i.e. DVMT, fuel consumption) to the percentage change in the variable of interest. These ratios are calculated as arc elasticities.

Elasticities were also computed for households grouped by population density, land use form, and household income. How the elasticity measures vary with respect to these groupings can provide useful insight into how the model is working. However, it is important to note that, since these results are simply tabulated from the household survey groupings, they do not necessarily show the joint effect of the two variables. The results are also influenced by correlated attributes.

This section reports these elasticities and compares them to results of several other studies. The purpose of these comparisons is to determine whether the sensitivities of the GreenSTEP models are within a reasonable range of results found by other studies. The purpose is not to achieve any particular elasticity targets because, in reality, there are no established targets. Different studies produce different elasticity estimates because of the way in which a study is done, and the data used will affect the results.

Studies differ from one another in several ways.[37] A basic difference is whether the model that is produced is based on longitudinal (time series) data or cross-sectional (single time) data. Longitudinal models directly estimate elasticity through the comparison of when and by how much the variables change over time. Cross-sectional models do not directly estimate elasticity but can be used to calculate elasticity by comparing how much model results change when an input variable such as fuel price is changed. Both short-term and long-term elasticities can be calculated with longitudinal studies. The results from cross-sectional modeling represent long-term elasticity.

Models also differ in the number of factors considered in the analysis. This is often the result of limitations in the data that are available. Longitudinal modeling studies typically consider many fewer variables than cross-sectional studies because of the lack of availability of time-series data.

Finally, models differ in the level of aggregation of the study units. The GreenSTEP models are very disaggregate because they model the responses of individual households to factors that affect vehicle travel. In contrast, the study units of many longitudinal models are much more aggregate (e.g. statewide VMT) because of data limitations.

Population Density Sensitivity

Table 79 shows elasticity estimates of household DVMT with respect to population density vary from -0.07 to -0.08 for density increases of 10% to 50%. In other words, a 50% increase in density would result in a 4 per cent decrease in average household DVMT. The elasticity is about 4 times higher in urban mixed type areas. These values are comparable to the findings of TRB Special Report 298:

> *Studies aimed at isolating the effect of residential density while controlling for sociodemographic and other land use variables consistently find that doubling density is associated with about 5 percent less VMT on average; one rigorous California study finds that VMT is lower by 12 percent. The same body of literature, mainly U.S.-based studies, reports that VMT is lower by an average of 3 to 20 percent when other land use factors that often accompany density, such as mixed uses, good design, and improved accessibility are accounted for, and suggests further that in some cases these reductions are additive.*[38]

Population density elasticity increases with increasing density and decreases with increasing income.

[37] Transportation Research Board, 2009. Add page/section reference

[38] Transportation Research Board, 2009. Add page/section reference

TABLE 79. POPULATION DENSITY ELASTICITY OF HOUSEHOLD DVMT: 10% TO 50% CHANGES IN CENSUS TRACT POPULATION DENSITY

	10% Density Change	20% Density Change	30% Density Change	40% Density Change	50% Density Change	N
Overall						
	-0.07	-0.07	-0.07	-0.08	-0.08	**9748**
Density (Population/ Square Mile)						
< 1,000	-0.01	-0.01	-0.01	-0.01	-0.01	**2356**
1,000 to 5,000	-0.04	-0.04	-0.04	-0.04	-0.05	**3502**
5,000 to 10,000	-0.12	-0.12	-0.13	-0.13	-0.14	**2935**
> 10,000	-0.37	-0.39	-0.41	-0.42	-0.44	**955**
Urban Form						
Urban Mixed Type	-0.20	-0.20	-0.21	-0.22	-0.23	**2726**
Other	-0.05	-0.05	-0.05	-0.06	-0.06	**7022**
Income (Thousand Dollars)						
0 to 40	-0.09	-0.09	-0.09	-0.10	-0.10	**3246**
40 to 80	-0.07	-0.07	-0.07	-0.07	-0.08	**3590**
80 Plus	**-0.06**	**-0.07**	**-0.07**	**-0.07**	**-0.07**	**2912**

Freeway Supply Sensitivity

Table 80 shows elasticity estimates of household DVMT with respect to freeway supply to vary from 0.06 to 0.07 for freeway supply increases from 10% to 50%. In other words, a 50% increase in freeway supply would result in a 3.5% increase in average household DVMT. Elasticity increases only slightly as the amount of change in freeway supply increases.

Elasticity decreases in higher density and urban mixed type areas. This seems reasonable because in higher density and urban mixed type areas, activities are located closer together and more modes of transportation are available, so the marginal effect of improvements in freeway travel times on auto mode choice and travel distance will be smaller.

Elasticity decreases slightly as income increases.

A large number of studies have been done to estimate the elasticity of vehicle travel with respect to road supply (lane-miles). There is a substantial amount of variation in the results, with elasticities ranging from 0.1 to 1.0.[39] This variation is a result of differences in the designs, assumptions, data and methodologies used in the studies.

[39] Strathman et al, 2000, Table 1.

Many of the studies are longitudinal and so evaluate the time relationships between road supply increases and VMT increases. Some of these studies also calculate high elasticity values and assume that, if road expansion occurs prior to VMT increases, then the effect must be causal from road supply to VMT. This assumption is questionable given that many road expansion projects are planned well in advance of construction and are sized to accommodate anticipated or planned development. Cervero[40] used a path analysis approach to capture the interdependencies between road supply, road speeds, travel demand, and development activity in order to better sort out causal effects. Using this approach, he estimated that increases in vehicle travel due to behavioral changes used 31 per cent of added capacity on average, and land use changes caused VMT increases using another 9 per cent. Other external factors, such as growth in population and income, used another 40 per cent, leaving 20 per cent of the capacity remaining.

TABLE 80. FREEWAY SUPPLY ELASTICITY OF HOUSEHOLD DVMT: 10% TO 50% CHANGES IN METROPOLITAN FREEWAY LANE-MILES PER CAPITA

	10% Ln-Mi Change	20% Ln-Mi Change	30% Ln-Mi Change	40% Ln-Mi Change	50% Ln-Mi Change	N
Overall						
	0.06	0.06	0.06	0.06	0.07	**9748**
Density (Population/ Square Mile)						
< 1,000	0.06	0.06	0.06	0.07	0.07	**2356**
1,000 to 5,000	0.06	0.06	0.06	0.06	0.07	**3502**
5,000 to 10,000	0.05	0.06	0.06	0. 06	0.06	**2935**
> 10,000	0.05	0.05	0.05	0. 06	0.06	**955**
Urban Form						
Urban Mixed Type	0.05	0.05	0.06	0.06	0.06	**2726**
Other	0.06	0.06	0.06	0.06	0.07	**7022**
Income (Thousand Dollars)						
0 to 40	0.06	0.06	0.07	0.07	0.07	**3246**
40 to 80	0.06	0.06	0.06	0.06	0.07	**3590**
80 Plus	**0.05**	**0.05**	**0.06**	**0.06**	**0.06**	**2912**

Strathman et al. developed a model from 1995 National Personal Travel Survey (NPTS) data that jointly determined population density, employment density, commute mode choice, and VMT.[41] The road supply elasticity of VMT estimated with their model was 0.29.

[40] Cervero, July 2001 and Spring 2003.

[41] Strathman et al, 2000.

Differences in elasticity estimates also result from differences in how VMT is counted. Studies that count VMT on one or more specific roadways or roadway types tend to produce higher elasticity estimates (ceteris paribus) because diverted traffic from uncounted facilities will be attributed to a VMT increase on the counted facilities. Corridor studies that count VMT on all roadways within a corridor help to control for the effect of traffic diversions, but still miss larger scale diversions from other corridors or other destinations. Metropolitan-wide studies that count VMT on all roads produce lower elasticity estimates because traffic shifts among routes and destinations will not bias the results. The GreenSTEP model estimates can be expected to be even lower because these estimates are based on changes in total household VMT, not just household VMT on metropolitan area roadways.

Estimates from studies also differ based on the modeling approach and the variables used in the model. This affects the results of observational studies because there is correlation between variables (although highly correlated variables are avoided) and so the estimated coefficient for any particular variable will depend on what other related variables are included in the model. For example, urban areas that have a more extensive freeway system also tend to be less dense and have less land use mixing. A model that includes freeway supply but excludes density and mixed use will have a larger coefficient on the freeway term than will a model which includes all three variables.

Finally, it should be noted that long term changes in VMT are due in part to changes in land development that occur in response to changes in the road system. For example, Cervero estimated that land use changes occurring as a result of roadway expansions accounted for the use of 9 per cent of added road capacity. Studies that measure this effect will produce higher elasticity estimates than studies that do not. The sensitivity test results reported here, unlike the Cervero and Strathman studies, do not consider any changes in land use as a result of freeway expansion. The key land use variables in the GreenSTEP models (population density and urban development type) are calculated from inputs to the model and are not determined endogenously.

In conclusion, the elasticity of travel with respect to freeway supply is low compared to numbers reported in the literature. However, since the studies behind the reports vary greatly in their geographic scope, other characteristics considered (economic, land use, demographic), and methodological approach, it hard to say whether the GreenSTEP model is insufficiently sensitive. The large geographic scope of the model, aggregate measurement of freeway supply, and inclusion of many variables, and disaggregate (household level) approach in GreenSTEP could greatly limit model sensitivity. However, even if the GreenSTEP model is not as sensitive as it should be the consequences in model application would be minimal because it is highly unlikely that any of the scenarios to be modeled will propose anything but minimal increases in freeway supply.

Transit Supply Sensitivity

Table 81 shows elasticity estimates of household DVMT with respect to transit supply to vary from -0.04 and -0.05 for transit supply increases from 10% to 50%. In other words, 50% increase in public transit revenue miles would result in a 2.5% decrease in average household DVMT.

TABLE 81. TRANSIT SUPPLY ELASTICITY OF HOUSEHOLD DVMT: 10% TO 50% INCREASES IN METROPOLITAN TRANSIT REVENUE MILES PER CAPITA

	10% Rev-Mi Change	20% Rev-Mi Change	30% Rev-Mi Change	40% Rev-Mi Change	50% Rev-Mi Change	N
Overall						
	-0.04	-0.05	-0.05	-0.05	-0.05	**9748**
Density (Population/ Square Mile)						
< 1,000	-0.01	-0.01	-0.01	-0.02	-0.02	**2356**
1,000 to 5,000	-0.03	-0.03	-0.03	-0.03	-0.03	**3502**
5,000 to 10,000	-0.07	-0.07	-0.07	-0.08	-0.08	**2935**
> 10,000	-0.21	-0.22	-0.23	-0.23	-0.24	**955**
Urban Form						
Urban Mixed Type	-0.11	-0.11	-0.12	-0.12	-0.13	**2726**
Other	-0.03	-0.04	-0.04	-0.04	-0.04	**7022**
Income (Thousand Dollars)						
0 to 40	-0.05	-0.05	-0.06	-0.06	-0.06	**3246**
40 to 80	-0.04	-0.04	-0.05	-0.05	-0.05	**3590**
80 Plus	**-0.04**	**-0.04**	**-0.05**	**-0.05**	**-0.05**	**2912**

As Table 81 shows, elasticity increases substantially at higher densities and in urban mixed use areas. This is sensible because higher densities and mixed use development make public transit more competitive with automobile travel by shortening travel distances and increasing transit access.

There transit supply elasticity decreases slightly with respect to income. The transit elasticities are consistent with the range of transit elasticities of driving to work estimated by Bento et al: -0.03 (excluding New York) to -0.07.[42]

[42] Bento et al, 2005, in Transportation Research Board 2009. In that study, transit supply is measured by route miles rather than revenue miles.

Household Income Sensitivity

Table 82 shows elasticity estimates of metropolitan household DVMT with respect to household income to be 0.28 for all income changes. In other words, a 50% increase in household income would result in a 14% increase in average household DVMT.

TABLE 82. INCOME ELASTICITY OF METROPOLITAN HOUSEHOLD DVMT: 10% TO 50% INCREASES IN HOUSEHOLD INCOME

	10% Income Change	**20% Income Change**	**30% Income Change**	**40% Income Change**	**50% Income Change**	**N**
Overall						
	0.28	0.28	0.28	0.28	0.28	**9748**
Density (Population/ Square Mile)						
< 1,000	0.28	0.28	0.28	0.28	0.28	**2356**
1,000 to 5,000	0.28	0.28	0.28	0.28	0.28	**3502**
5,000 to 10,000	0.29	0.29	0.29	0.29	0.29	**2935**
> 10,000	0.31	0.31	0.31	0.31	0.31	**955**
Urban Form						
Urban Mixed Type	0.30	0.30	0.30	0.30	0.30	**2726**
Other	0.28	0.28	0.28	0.28	0.28	**7022**
Income (Thousand Dollars)						
0 to 40	0.33	0.33	0.33	0.32	0.32	**3246**
40 to 80	0.28	0.28	0.28	0.28	0.28	**3590**
80 Plus	**0.27**	**0.27**	**0.27**	**0.27**	**0.27**	**2912**

There is a small increase in income elasticity as population density increases.

These income elasticity estimates are lower, but not greatly so, than the range of income elasticities (0.35 – 0.37) computed previously by Pickrell and Schimek from 1995 NPTS data.[43]

Table 83 shows elasticity estimates of non-metropolitan household DVMT with respect to household income to be close to the estimates for metropolitan households.

[43] Don Pickrell and Paul Schimek, Trends in Personal Motor Vehicle Ownership and Use: Evidence from the Nationwide Personal Transportation Survey, U.S. DOT Volpe Center, Cambridge, MA, April 23, 1998, https://nhts.ornl.gov/1995/Doc/Envecon.pdf

TABLE 83. INCOME ELASTICITY OF NON-METROPOLITAN HOUSEHOLD DVMT: 10% TO 50% INCREASES IN HOUSEHOLD INCOME

	10% Income Change	**20% Income Change**	**30% Income Change**	**40% Income Change**	**50% Income Change**	**N**
Overall						
	0.28	0.28	0.28	0.28	0.28	**9312**
Density (Population/ Square Mile)						
< 1,000	0.28	0.28	0.28	0.28	0.28	**6217**
1,000 to 5,000	0.27	0.27	0.27	0.27	0.27	**2321**
5,000 to 10,000	0.29	0.29	0.29	0.29	0.29	**733**
> 10,000	0.33	0.33	0.33	0.32	0.32	**50**
Urban Form						
Urban Mixed Type	0.28	0.28	0.28	0.28	0.28	**9232**
Other	0.28	0.28	0.28	0.28	0.28	**89**
Income (Thousand Dollars)						
0 to 40	0.32	0.31	0.31	0.31	0.31	**4725**
40 to 80	0.26	0.26	0.26	0.26	0.26	**3303**
80 Plus	**0.25**	**0.25**	**0.25**	**0.25**	**0.25**	**1293**

Fuel Price Sensitivity

Table 84 shows fuel price elasticity estimates of metropolitan household DVMT to vary from -0.01 and -0.02 for fuel price changes between 10% and 50%. Table 85 shows elasticity to vary between -0.05 and -0.29 for fuel price changes between 100% and 500%.

Elasticities increase as prices increase because as a consequence of the approach taken in GreenSTEP to account for the effects of costs on vehicle travel. This approach replicates recent trends which showed very little change in vehicle travel in response to increases in gas prices, but also is responsive to large increases in gas (or other) prices.

Table 86 and 87 show fuel price elasticity estimates of non-metropolitan household DVMT. The overall elasticity values are higher than for metropolitan households. Moreover, fuel price elasticity for these households varies much more with household income.

TABLE 84. FUEL PRICE ELASTICITY OF METROPOLITAN HOUSEHOLD DVMT: GIVEN 20 AND 40 PERCENT CHANGES IN FUEL PRICE

	10% Price Change	**20% Price Change**	**30% Price Change**	**40% Price Change**	**50% Price Change**	**N**
Overall						
	-0.01	-0.01	-0.02	-0.02	-0.02	**9748**
Density (Population/ Square Mile)						
< 1,000	-0.02	-0.02	-0.02	-0.03	-0.03	**2356**
1,000 to 5,000	-0.01	-0.01	-0.02	-0.02	-0.02	**3502**
5,000 to 10,000	-0.01	-0.01	-0.01	-0.02	-0.02	**2935**
> 10,000	-0.01	-0.01	-0.01	-0.01	-0.01	**955**
Urban Form						
Urban Mixed Type	-0.01	-0.01	-0.01	-0.01	-0.02	**2726**
Other	-0.01	-0.02	-0.02	-0.02	-0.03	**7022**
Income (Thousand Dollars)						
0 to 40	-0.05	-0.06	-0.07	-0.07	-0.08	**3246**
40 to 80	-0.00	-0.01	-0.01	-0.01	-0.02	**3590**
80 Plus	**-0.00**	**-0.00**	**-0.00**	**-0.00**	**-0.00**	**2912**

TABLE 85. FUEL PRICE ELASTICITY OF METROPOLITAN HOUSEHOLD DVMT: GIVEN 100 TO 500 PER CENT CHANGES IN FUEL PRICE

	100% Price Change	**200% Price Change**	**300% Price Change**	**400% Price Change**	**500% Price Change**	**N**
Overall						
	-0.05	-0.1	-0.16	-0.23	-0.29	**9748**
Density (Population/ Square Mile)						
< 1,000	-0.06	-0.13	-0.21	-0.29	-0.35	**2356**
1,000 to 5,000	-0.04	-0.09	-0.15	-0.22	-0.28	**3502**
5,000 to 10,000	-0.04	-0.09	-0.14	-0.20	-0.26	**2935**
> 10,000	-0.02	-0.05	-0.08	-0.12	-0.16	**955**
Urban Form						
Urban Mixed Type	-0.03	-0.07	-0.11	-0.15	-0.20	**2726**
Other	-0.05	-0.10	-0.17	-0.24	-0.30	**7022**
Income (Thousand Dollars)						
0 to 40	-0.13	-0.24	-0.34	-0.42	-0.49	**3246**
40 to 80	-0.04	-0.10	-0.17	-0.25	-0.32	**3590**
80 Plus	**-0.01**	**-0.04**	**-0.08**	**-0.13**	**-0.18**	**2912**

TABLE 86. FUEL PRICE ELASTICITY OF NON-METROPOLITAN HOUSEHOLD DVMT: GIVEN 20 AND 40 PERCENT CHANGES IN FUEL PRICE

	10% Price Change	20% Price Change	30% Price Change	40% Price Change	50% Price Change	N
Overall						
	-0.03	-0.04	-0.05	-0.06	-0.06	**9321**
Density (Population/ Square Mile)						
< 1,000	-0.04	-0.05	-0.06	-0.06	-0.07	**6217**
1,000 to 5,000	-0.02	-0.02	-0.03	-0.03	-0.04	**2321**
5,000 to 10,000	-0.03	-0.03	-0.04	-0.04	-0.04	**733**
> 10,000	-0.05	-0.05	-0.05	-0.05	-0.05	**50**
Urban Form						
Urban Mixed Type	-0.01	-0.02	-0.02	-0.03	-0.04	**89**
Other	-0.03	-0.04	-0.05	-0.06	-0.06	**9232**
Income (Thousand Dollars)						
0 to 40	-0.08	-0.09	-0.10	-0.12	-0.13	**4725**
40 to 80	-0.01	-0.02	-0.02	-0.02	-0.03	**3303**
80 Plus	**-0.01**	**-0.01**	**-0.01**	**-0.02**	**-0.02**	**1293**

TABLE 87. FUEL PRICE ELASTICITY OF NON-METROPOLITAN HOUSEHOLD DVMT: GIVEN 100 AND 500 PERCENT CHANGES IN FUEL PRICE

	100% Price Change	200% Price Change	300% Price Change	400% Price Change	500% Price Change	N
Overall						
	-0.1	-0.2	-0.28	-0.36	-0.43	**9321**
Density (Population/ Square Mile)						
< 1,000	-0.12	-0.22	-0.31	-0.40	-0.46	**6217**
1,000 to 5,000	-0.07	-0.14	-0.22	-0.29	-0.36	**2321**
5,000 to 10,000	-0.07	-0.13	-0.19	-0.26	-0.32	**733**
> 10,000	-0.07	-0.11	-0.15	-0.20	-0.24	**50**
Urban Form						
Urban Mixed Type	-0.07	-0.13	-0.20	-0.27	-0.34	**89**
Other	-0.10	-0.20	-0.28	-0.36	-0.43	**9232**
Income (Thousand Dollars)						
0 to 40	-0.21	-0.34	-0.45	-0.54	-0.60	**4725**
40 to 80	-0.06	-0.15	-0.24	-0.33	-0.40	**3303**
80 Plus	**-0.03**	**-0.07**	**-0.12**	**-0.18**	**-0.24**	**1293**

A large number of studies have been done to estimate the elasticity of vehicle travel and fuel consumption to changes in fuel price. An unpublished study by Dong, Hunt and Weidner for ODOT summarizes the literature on this subject.[44] Highlights include:

- Goodwin (2004) estimated the average long run fuel price elasticity of vehicle travel to be -0.29 based on a review of 69 international studies published after 1990.
- Goodwin also found the fuel price elasticity to vehicle travel to be decreasing over time as follows:
    - Pre-1974: -0.54
    - 1974-1981: -0.32
    - Post-1981: -0.24
- de Jong and Gun (2001) estimated the average long run fuel price elasticity of vehicle travel to be -0.26 based on a review of 50 international studies published after 1985.
- Kennedy and Wallis (2007) estimated the fuel price elasticity of urban off peak car traffic after two years to be -0.36 and corresponding elasticities of urban peak and rural traffic to be -0.24 and -0.19, respectively.

The results of fuel price elasticity studies, as with other elasticity studies, depend on the study methods. Many of these studies are longitudinal studies using aggregate data. In contrast, the GreenSTEP models are based on highly disaggregate cross-sectional data. Pickrell and Schimek estimated elasticities using a cross-sectional model based on 1995 NPTS data. Depending on the model structure, they estimated elasticity values in the range of -0.19 to -0.32.[45]

More recent longitudinal studies (after 2001) of the fuel price elasticity of fuel consumption and VMT estimated much lower short run elasticities than previously. Hughes, Knittel and Sperling estimated the short-range fuel price elasticities of fuel consumption to range from -0.034 to -0.077 from 2001-2006.[46] The U.S. Congressional Budget Office (CBO) estimated that a 10 per cent increase in fuel price reduced VMT by 0.2 to 0.3 percent in the short run and 1.1 to 1.5 percent in the long run.[47] Small and Van Dender, estimated short run fuel price elasticity of -0.02 to -0.03 and a long run elasticity of -0.11 to -0.15.[48]

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[44] Dong, Hongwei, et al, 2010.

[45] Pickrell, Don and Paul Schimek, 1998,. p. 32.

[46] Hughes, Jonathan E. et al, 2008, pp. 93-114.

[47] U.S. Congressional Budget Office, 2008.

[48] U.S. Department of Transportation, “Transportation’s Role in Reducing U.S. Greenhouse Gas Emissions, Volume 1: Synthesis Report”, Report to Congress, April 2010, p. 3-15.

These more recent findings are consistent with the findings in the earlier section on the household budget approach to modeling the effects of prices in GreenSTEP.

Fuel Economy Sensitivity

The elasticities of DVMT and fuel consumption with respect to fuel economy for metropolitan and non-metropolitan area households are shown in Table 88 and Table 89 respectively. The magnitude of the fuel consumption elasticity is dependent on the travel rebound effect that occurs because the cost of travel is reduced. Since the effect of cost on travel depends on the magnitude of the cost, elasticities were calculated at base year (2001) fuel prices and at 4 times the base year prices.

Table 88. Fuel Economy Elasticity of Metropolitan Household DVMT: 10% to 50% Increases in Fuel Economy

	10% MPG Change	20% MPG Change	30% MPG Change	40% MPG Change	50% MPG Change
Base Gas Price					
DVMT	0.01	0.01	0.01	0	**0**
Fuel	-0.99	-0.99	-0.99	-0.99	**-0.99**
4 X Base Price					
DVMT	0.37	0.35	0.32	0.31	**0.29**
Fuel	**-0.61**	**-0.64**	**-0.66**	**-0.68**	**-0.7**

Table 89. Fuel Economy Elasticity of Non-Metropolitan Household DVMT: 10% to 50% Increases in Fuel Economy

	10% MPG Change	20% MPG Change	30% MPG Change	40% MPG Change	50% MPG Change
Base Gas Price					
DVMT	0.02	0.02	0.02	0.02	**0.02**
Fuel	-0.97	-0.98	-0.98	-0.98	**-0.98**
4 X Base Price					
DVMT	0.55	0.53	0.5	0.48	**0.46**
Fuel	**-0.43**	**-0.46**	**-0.48**	**-0.51**	**-0.53**

It can be seen that at base year fuel prices, the effects of improvements to fuel economy are predicted to have minimal effects on household vehicle travel. Almost all of the improvements would go into reduced fuel consumption. This is consistent with the observation that fuel prices had minimal effects on vehicle travel in the recent past.

As expected, the rebound effect is much greater at 4 times the base year fuel cost. A 50% increase in average fuel economy would result in a 14.5% increase in VMT in metropolitan areas and a 23% increase in non-metropolitan areas. The greater fuel economy elasticity of fuel consumption at higher fuel prices is a direct consequence to budget model approach. This approach is also responsible for the decline in estimated elasticities as the magnitude of the fuel economy improvement increases. The fuel economy elasticity is greater for non-metropolitan households than metropolitan households because the fuel price elasticity for non-metropolitan households is greater as well.

Congestion Model Sensitivity Testing

Several tests of the new model were performed in order to determine whether it performs reasonably. Portland metropolitan area reference case forecast values for 2035 were used as the starting point for the test. The new congestion emissions model was run over ranges for various attributes as follows:

- Congestion prices for freeway DVMT in severe and extreme congestion bins were varied from 0 to 50 cents per mile.
- Congestion prices for both freeway and arterial DVMT in severe and extreme congestion bins were varied from 0 to 50 cents per mile.
- Freeway and arterial per capita lane miles (i.e. lane miles per 1000 people) were varied jointly over ranges of 0.1 to 0.5 and 0.8 to 1.6 respectively.
- Freeway operations programs were varied from zero implementation to full implementation.
- Arterial operations programs were varied from zero implementation to full implementation.
- Traffic smoothing was varied from zero implementation to full implementation.

It should be noted that these tests only used the congestion and emissions model described in this paper. The full GreenSTEP model was not run so the results do not show the effect of congestion pricing on the amounts of household vehicle travel.

Congestion Pricing Tests

Two sets of tests of congestion pricing were made. In the first set, freeway DVMT at severe and extreme congestion levels was priced at rates varying from 0 to 50 cents per mile. In the second set, both freeway and arterial DVMT at severe and extreme congestion levels were priced at those rates.

Table 90 shows the percentage change in freeway DVMT corresponding to each pricing level. The model predicts a substantial shift in DVMT from freeways to arterials. This is to be expected and consistent with observed behavior that pricing only some facilities shifts some travel to unpriced facilities. The model predicts a smaller shift in DVMT when congestion on freeways and arterials is priced equally. Equal pricing does not eliminate the DVMT shift, however, because speeds on freeways and arterials differ and so relationship of money paid for pricing to money value of congestion differs.

The effect of pricing on freeway and arterial DVMT is shown in Figure 87. The greater shift of DVMT from freeways to arterials with freeway-only pricing can be seen. It should be noted that total DVMT does not change because these tests did not include the budget effect on household travel.

TABLE 90. PERCENTAGE REDUCTION IN FREEWAY LIGHT-DUTY VEHICLE DVMT AT VARIOUS CONGESTION PRICE LEVELS

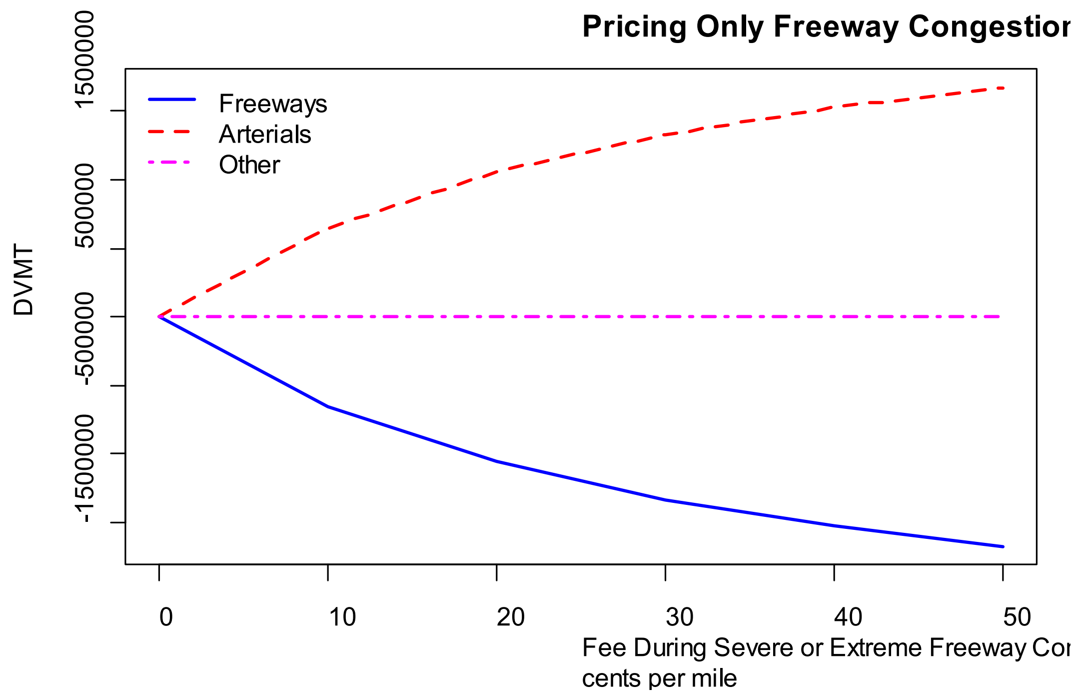
Price Per Mile for Travel in Severe or Extreme Congestion	Percentage Change in Freeway DVMT	
	Freeway Only Pricing	Freeway and Arterial Pricing
$ 0.00	0	0
$ 0.10	-5.9	-2.9
$ 0.20	-9.5	-4.8
$ 0.30	-12.0	-6.2
$ 0.40	-13.8	-7.2
$ 0.50	-15.1	-7.9

Table 91 shows the effect of pricing on total freeway and arterial VHT. As can be seen, the changes in VHT are much smaller than the changes in DVMT. Figure 88 helps to explain this result. With freeway-only pricing, a substantial reduction in freeway VHT is offset by an almost equal increase in arterial VHT as some travel shifts away from priced roads to unpriced roads. The reduction is greater when both freeways and arterials are priced because of less shifting from freeways to arterials, but the freeway VHT reduction is limited because of the limited shifting. The effect on truck VHT is more pronounced, as can be seen in Table 91, because trucks are assumed to not shift routes in response to congestion pricing.

TABLE 91. PERCENTAGE REDUCTION IN TOTAL FREEWAY AND ARTERIAL VHT AT VARIOUS CONGESTION PRICE LEVELS

Price Per Mile for Travel in Severe or Extreme Congestion	Percentage Change in Freeway & Arterial VHT			
	Freeway Only Pricing		Freeway and Arterial Pricing	
	Light-Duty	Heavy Truck	Light-Duty	Heavy Truck
$ 0.00	0	0	0	0
$ 0.10	-0.1	-1.3	-0.4	-1.1
$ 0.20	-0.4	-2.5	-0.9	-2.0
$ 0.30	-0.7	-3.5	-1.3	-2.8
$ 0.40	-1.0	-4.4	-1.7	-3.6
$ 0.50	-1.2	-5.1	-2.1	-4.2

Figure 87. Modeled Effect of Congestion Pricing on the Change in Freeway and Arterial DVMT Relative to No-Pricing Scenario



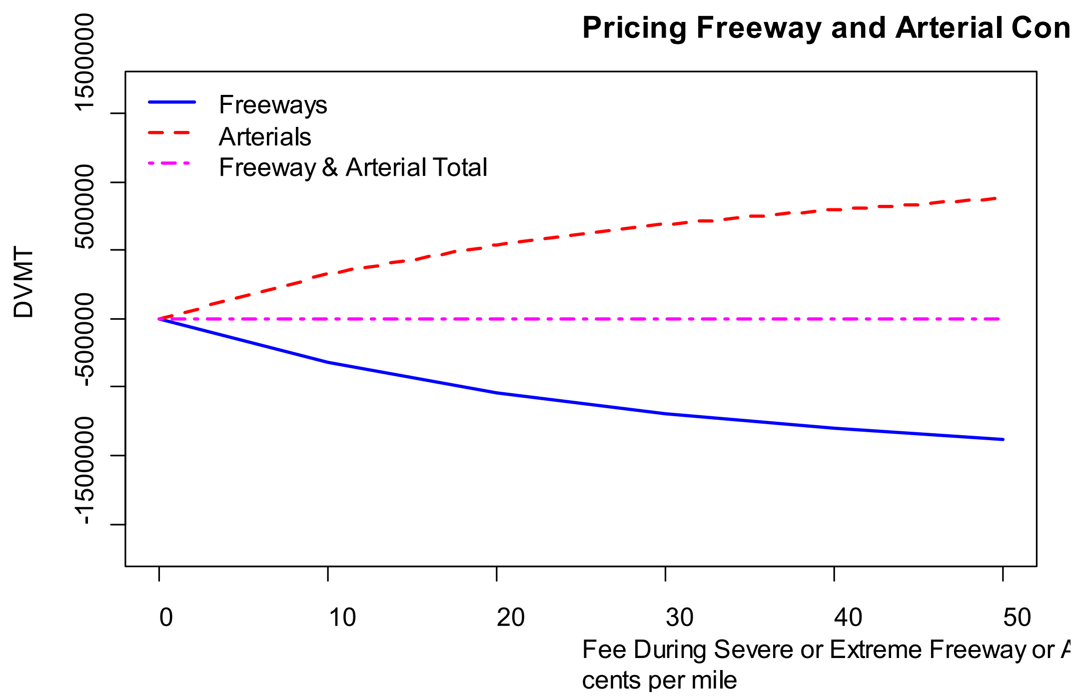
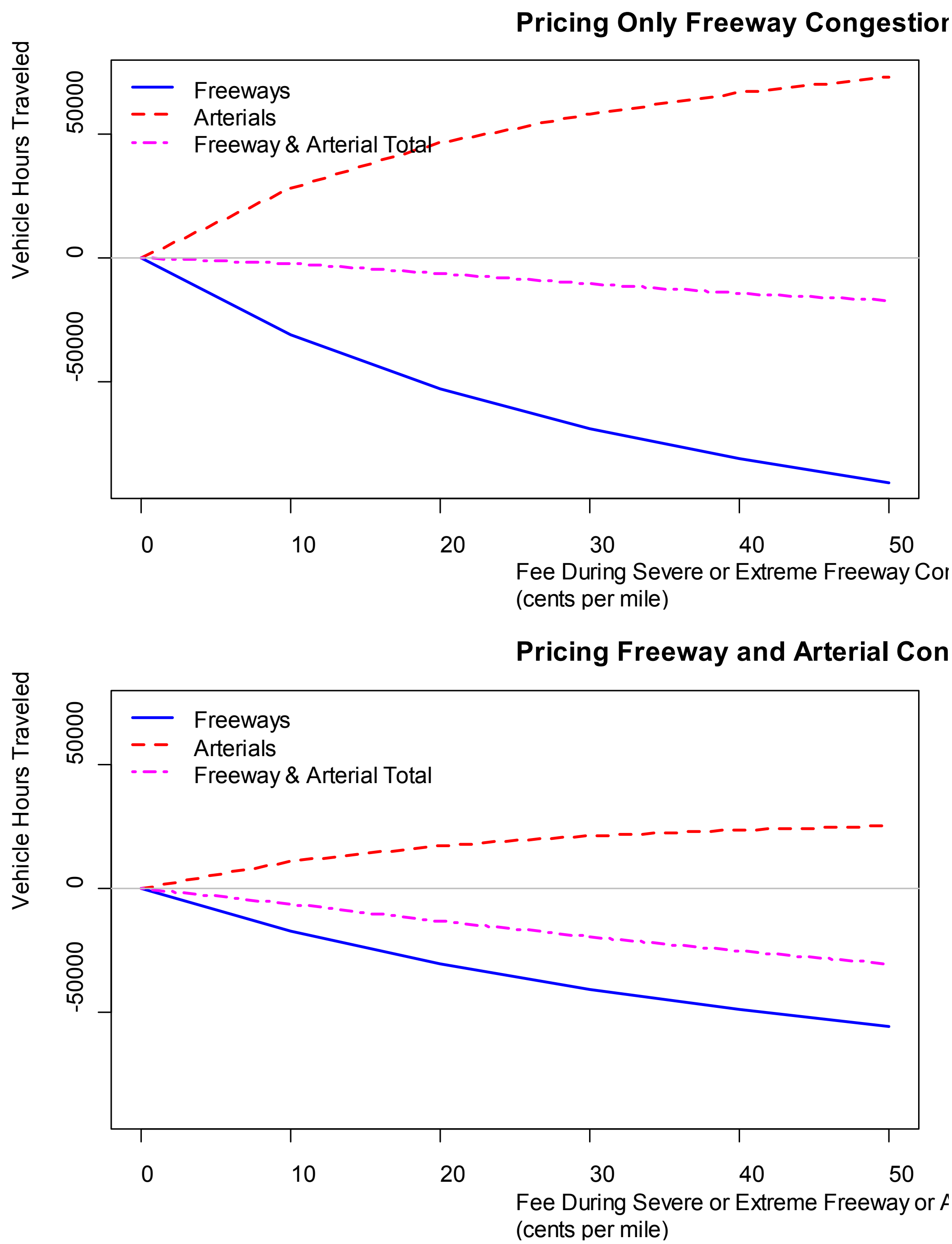


FIGURE 88. MODELED EFFECT OF CONGESTION PRICING ON THE CHANGE IN FREEWAY AND ARTERIAL VHT RELATIVE TO NO-PRICING SCENARIO



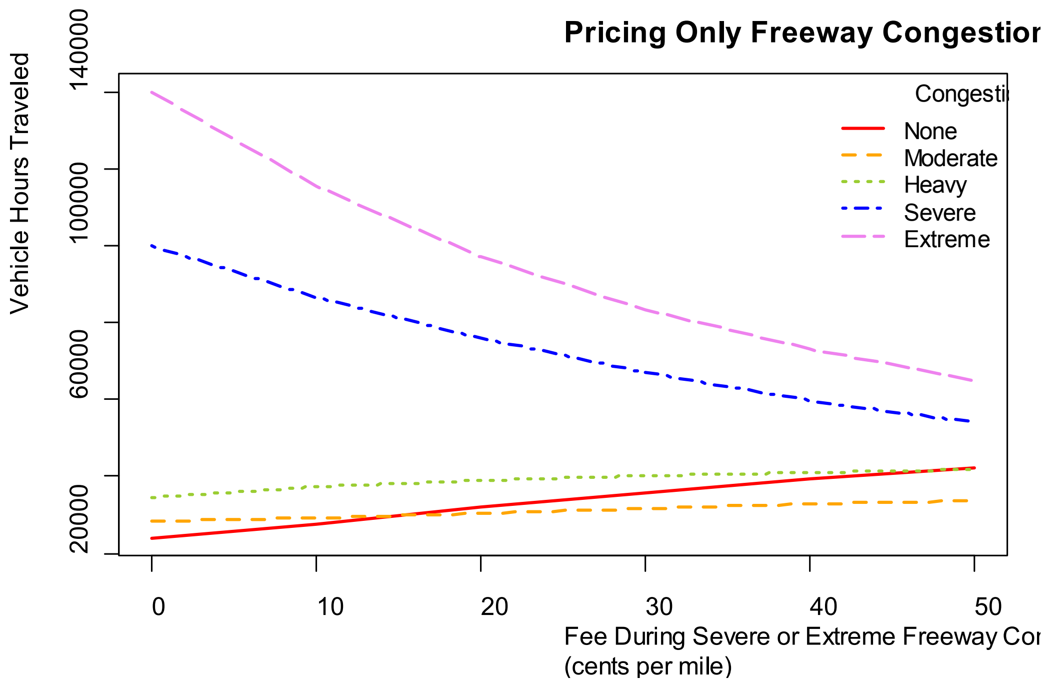
Figures 89 and 90 show the effects of freeway and arterial pricing on VHT by congestion level for freeways and arterials respectively. Figure 89 shows that changes in the amounts of VHT by congestion level change sensibly as pricing increases. Pricing is only applied to DVMT occurring at severely or extremely congested level and it can be seen that the VHT occurring at those decreases while VHT occurring at the other congestion levels increases. The reductions are greatest for freeways when only freeways are priced.

Figure 90 shows that when only freeways are priced, VHT at all congestion levels increases on arterials. However when arterials are priced, VHT at severe and extreme congestion levels decreases while VHT at lower congestion levels increases.

Figure 91 shows the modeled effects of congestion pricing on the efficiency of vehicles with different powertrains.[49] It should be noted that the size of changes are very small as indicated by the scale of the y-axis. When arterials are not priced, only ICE powertrain vehicles have improved fuel economy, while the efficiency of electric vehicles declines. Heavy trucks gain the most improvement. When arterials are priced, HEVs see a very slight improvement in efficiency. These results reflect the fact that the efficiency of EVs and to a lesser extent HEVs is less affected by congestion and more affected by the vehicle drag that accompanies higher speed travel.

[49] The congestion efficiency for all vehicle powertrains was set at 0.5.

FIGURE 89. MODELED EFFECT OF CONGESTION PRICING ON FREEWAY VHT BY CONGESTION CATEGORY



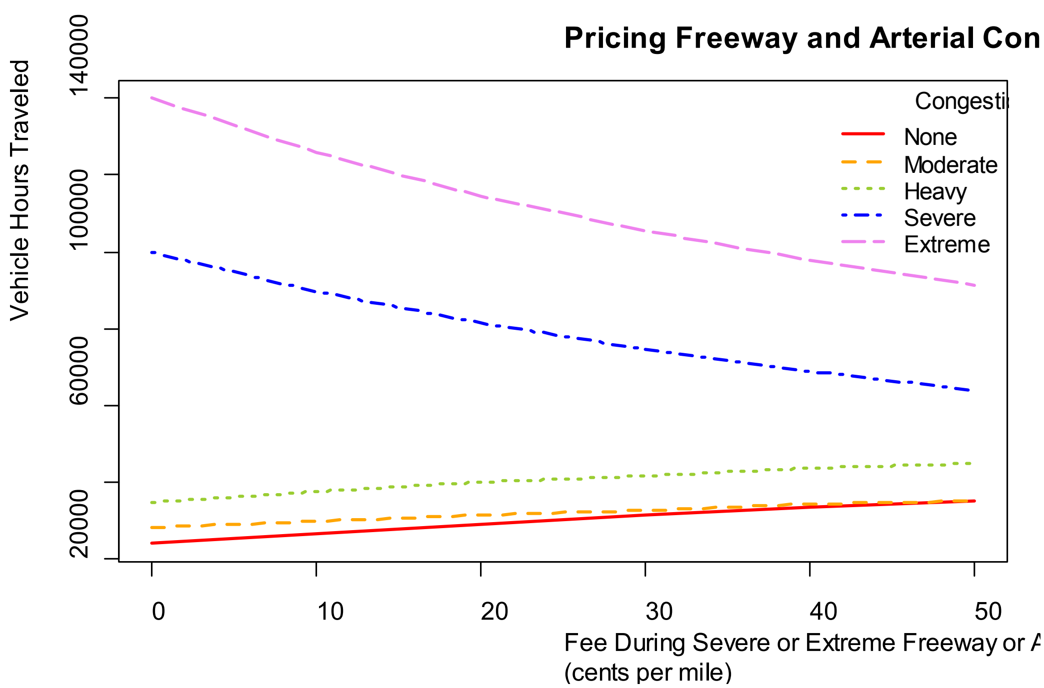


FIGURE 90. MODELED EFFECT OF CONGESTION PRICING ON ARTERIAL VHT BY CONGESTION CATEGORY

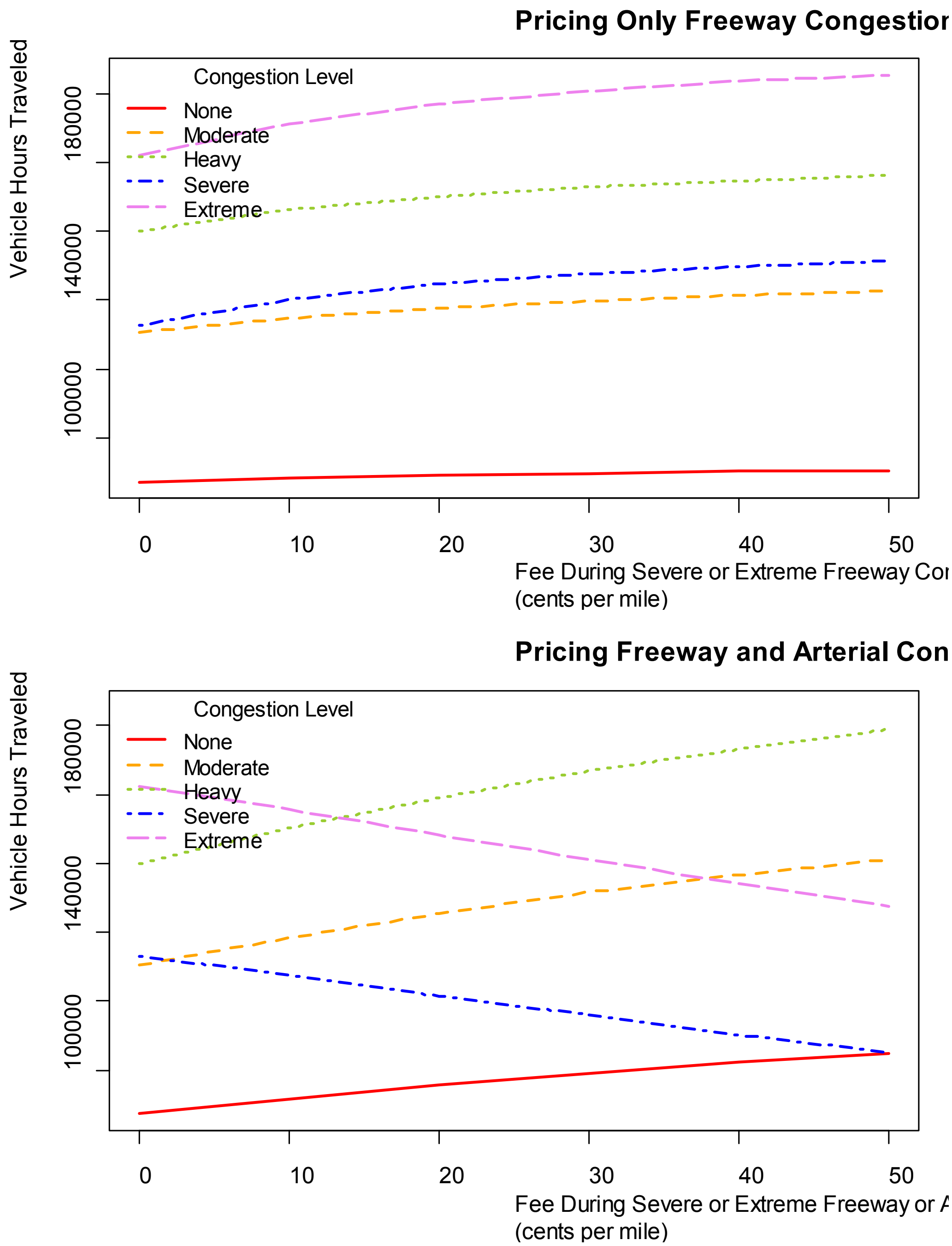
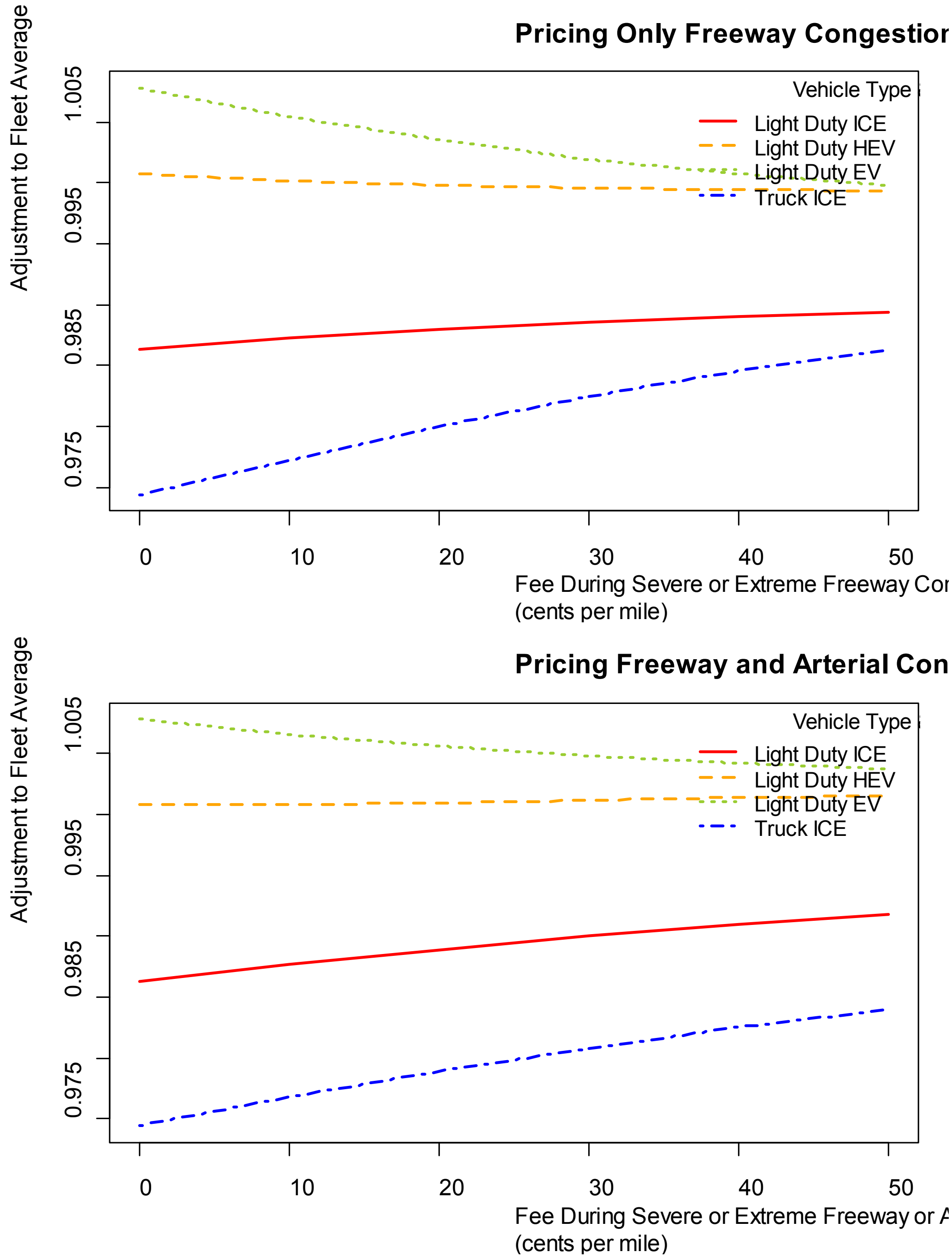


FIGURE 91. MODELED EFFECT OF CONGESTION PRICING ON ADUSTMENTS TO AVERAGE VEHICLE EFFICIENCY



Freeway and Arterial Capacity Tests

The modeled effects of different combinations of freeway and arterial capacities (e.g. lane-miles) on average speeds are shown in Figure 92. Speeds are shown for light vehicles, trucks and buses in different panels. Freeway supply levels are shown by different lines in each panel. Arterial supply levels are shown on the x axis of each panel. It should be noted that average truck speeds are higher than average light vehicle speeds because more truck travel occurs on freeways than arterials while the opposite is the case for light vehicles. Bus speeds a lower because of the high percentage of bus travel on arterials or lower functionally classed roads and because of the frequent stops buses make to pick up and drop off passengers.

It can be seen that freeway capacity has much more of an effect than arterial capacity on speed. That's because arterials operate over a much narrower range of speeds between uncongested and congested conditions. The change in speeds is also moderated by the shifting traffic loads on freeways and arterials due to changes in speed.

It can also be seen that changes in average speeds in response to freeway capacity are greater when freeway capacity is higher than when freeway capacity is low. That is due to:

- Smaller differences in average speeds between higher congestion levels than between lower congestion levels;
- Smaller differences between freeway and arterial speeds at higher congestion levels than lower congestion levels; and
- DVMT shifts between freeways and arterials as capacity changes.

Figures 93 through 95 show the effects of freeway and arterial capacity on vehicle efficiency. The same scales are used for all of the charts so they can all be easily compared. Several patterns are evident:

- Vehicle efficiency is relatively insensitive to changes in capacity (i.e. congestion).
- As the congestion efficiency of vehicles increases, less improvement in vehicle efficiency occurs as congestion decreases.
- The efficiency of HEV powertrains is less affected by congestion than ICE powertrains. The efficiency of EV powertrains is affected even less.
- At higher levels of congestion efficiency, vehicle efficiency decreases as capacity increases. This only occurs at high levels of congestion efficiency for ICE engines but occurs at a much lower level for EVs. The performance for HEVs is in between in this regard.

Figure 92. Modeled Effect of Freeway and Arterial Lane-Miles on Average Vehicle Speeds

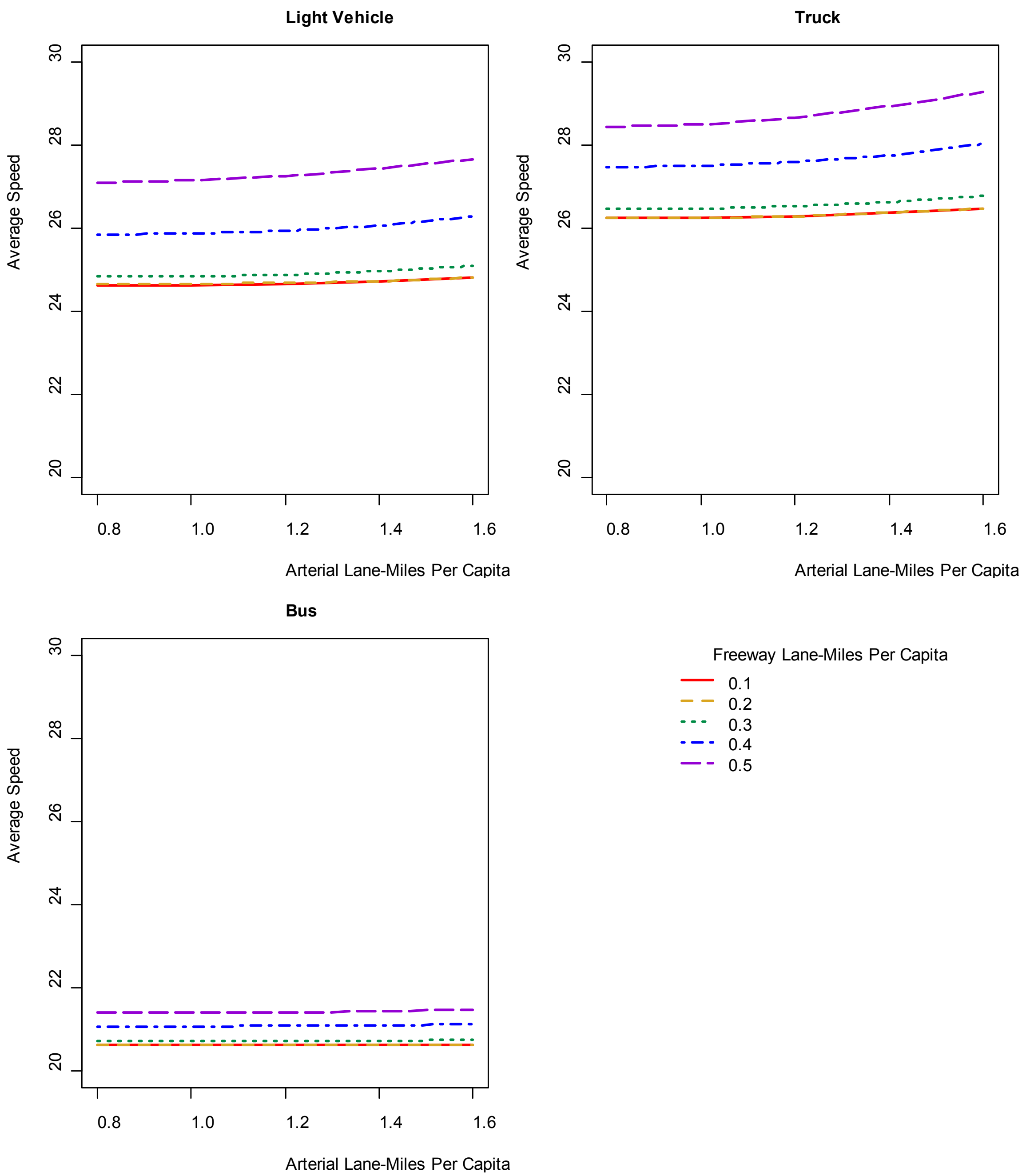


Figure 93. Modeled Effect of Freeway and Arterial Lane-Miles and Congestion Efficiency on Adjustments to Average Vehicle Efficiency of ICE Powertrains

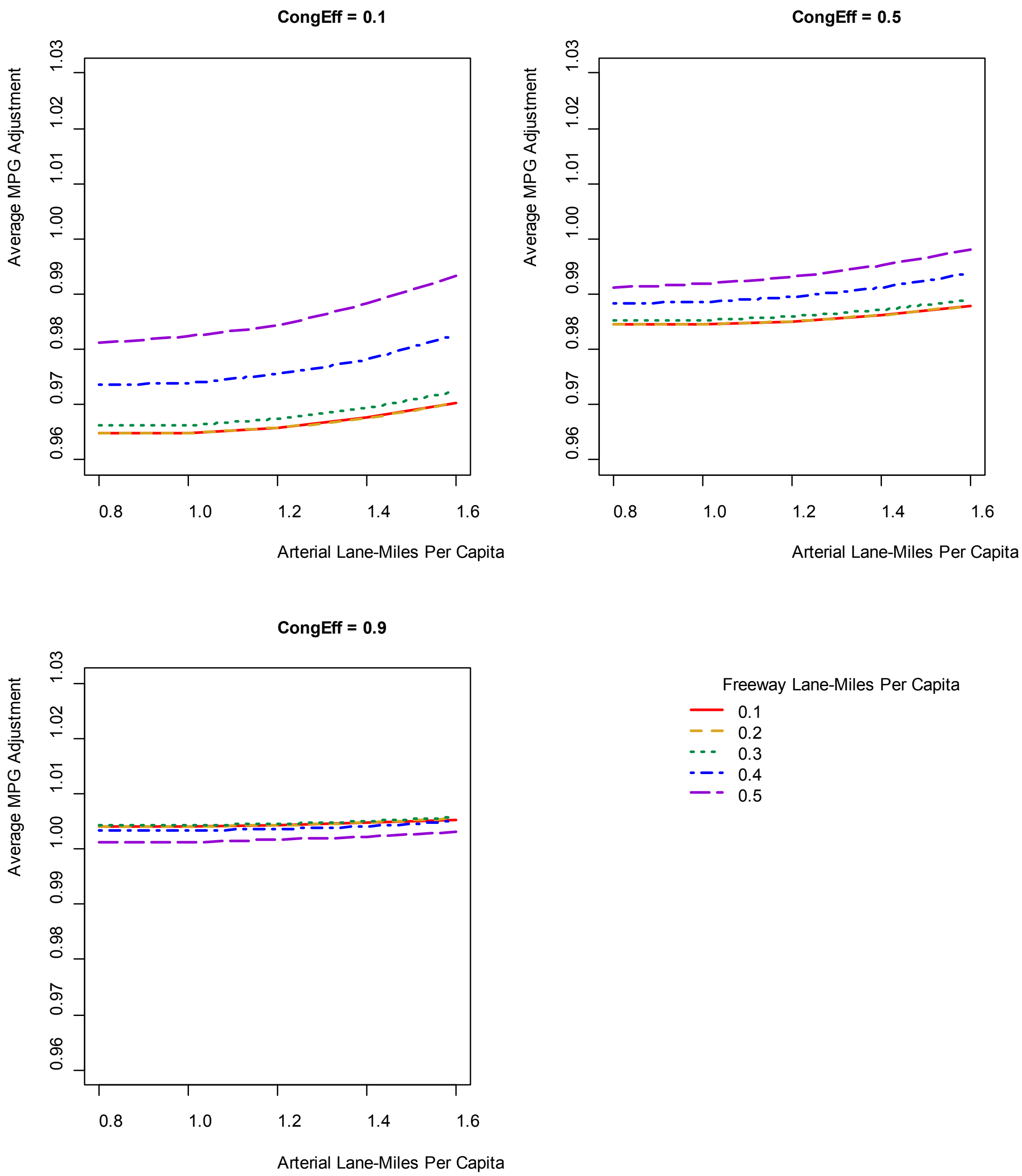


FIGURE 94. MODELED EFFECT OF FREEWAY AND ARTERIAL LANE-MILES AND CONGESTION EFFICIENCY ON ADJUSTMENTS TO AVERAGE VEHICLE EFFICIENCY OF HEV POWERTRAINS

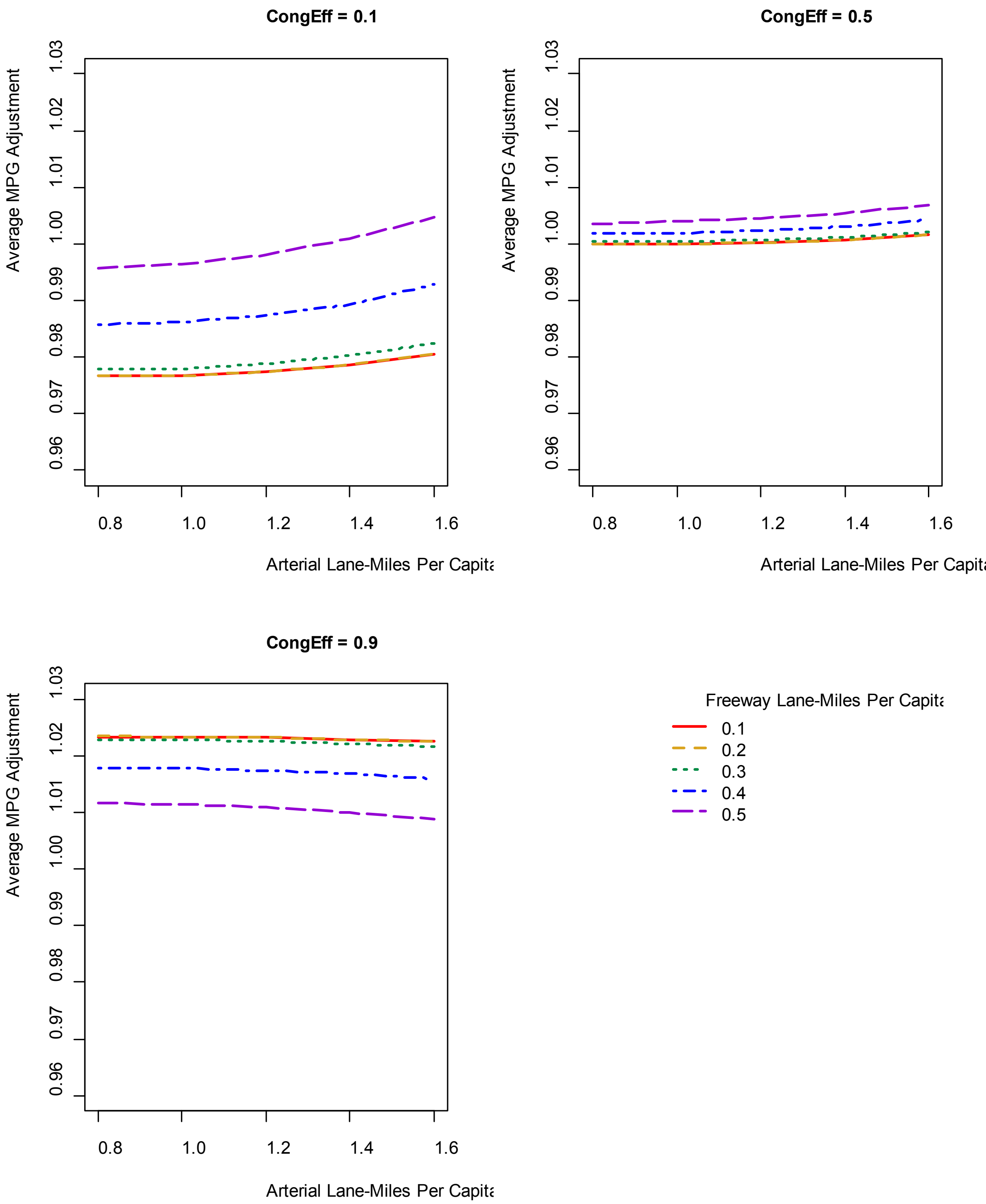
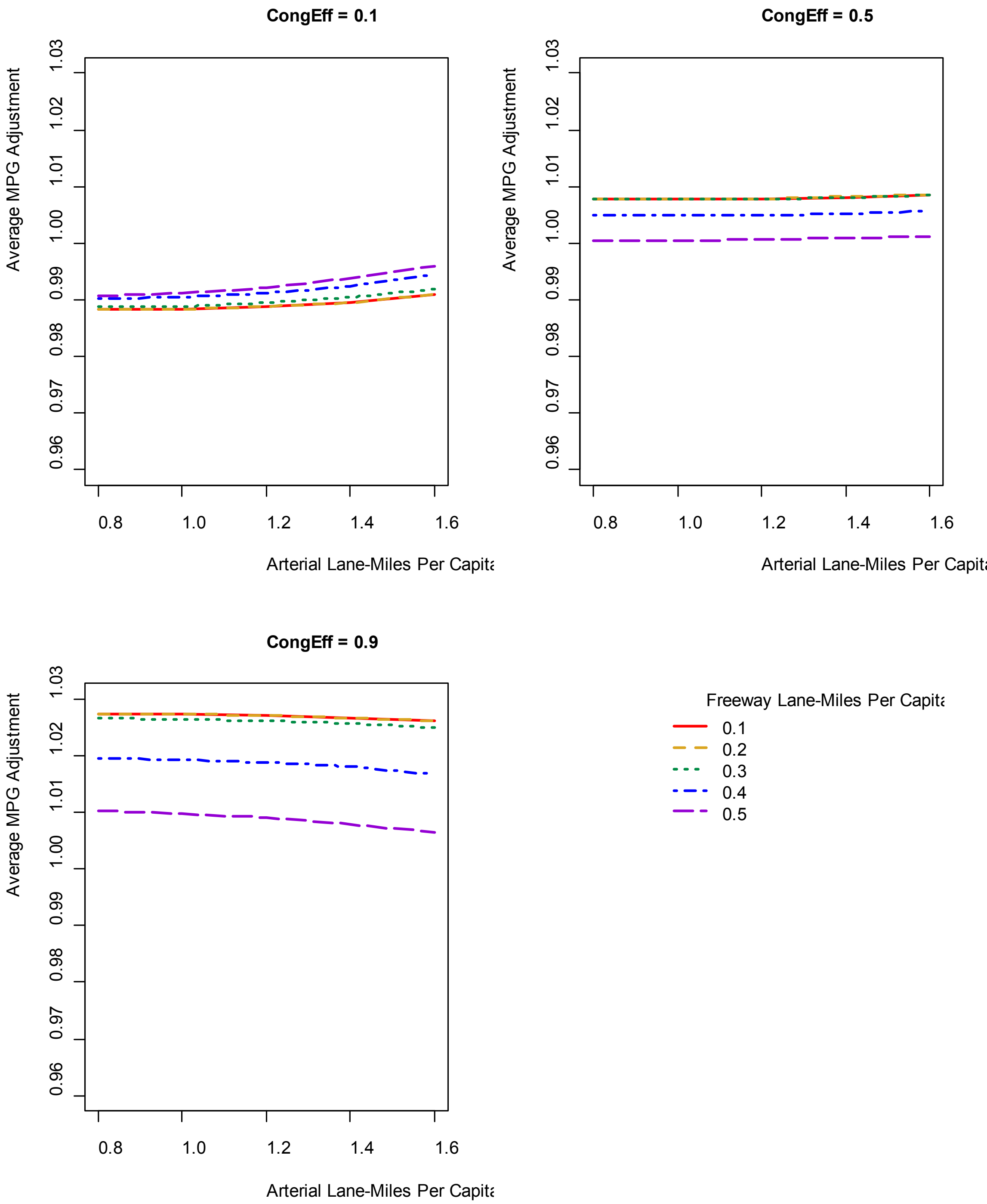


FIGURE 95. MODELED EFFECT OF FREEWAY AND ARTERIAL LANE-MILES AND CONGESTION EFFICIENCY ON ADJUSTMENTS TO AVEARGE VEHICLE EFFICIENCY OF EV POWERTRAINS



Freeway and Arterial Operations and Traffic Smoothing Tests

The modeled effects of different levels of operations program deployments for freeways and arterials are shown in Figures 96 and 97 respectively.

Figure 96 shows the effects of varying freeway ramp metering and incident management from no deployment to maximum deployment. It can be seen from the first chart that the average freeway speed is over 1.5 MPH faster at full deployment than at no deployment. Arterial speeds increase very slightly. The second chart shows that deploying freeway operations programs shifts DVMT from arterials to freeways. This is to be expected and shows that the model responds correctly to actions that increase travel speeds. The increase in freeway speeds causes shifting of some traffic from arterials to freeways and that in turn dampens the amount of freeway speed increase and causes some arterial speed increase. The third chart shows that vehicle efficiencies change very slightly.

Figure 97 shows the effects of varying arterial signal coordination and access management from no deployment to maximum deployment. The first chart shows that both arterial and freeway speeds increase with greater deployment of these programs. The change is small however; about one third of a mile per hour on arterials. The second graph shows that increasing the average arterial speeds causes traffic to shift from freeways to arterials (as expected). Finally, as with freeway operations improvements, there is very little effect on vehicle efficiency.

Figure 98 shows the results of varying the levels of traffic smoothing from no smoothing to maximum possible smoothing. It can be seen that traffic smoothing greatly increases the efficiencies of light duty and truck ICE powertrains. It has no effect on moderate efficiency light duty HEV and EV powertrains.

FIGURE 96. MODELED EFFECT OF FREEWAY OPERATIONS PROGRAMS ON FREEWAY AND ARTERIAL SPEEDS, DVMT AND VEHICLE EFFICIENCY

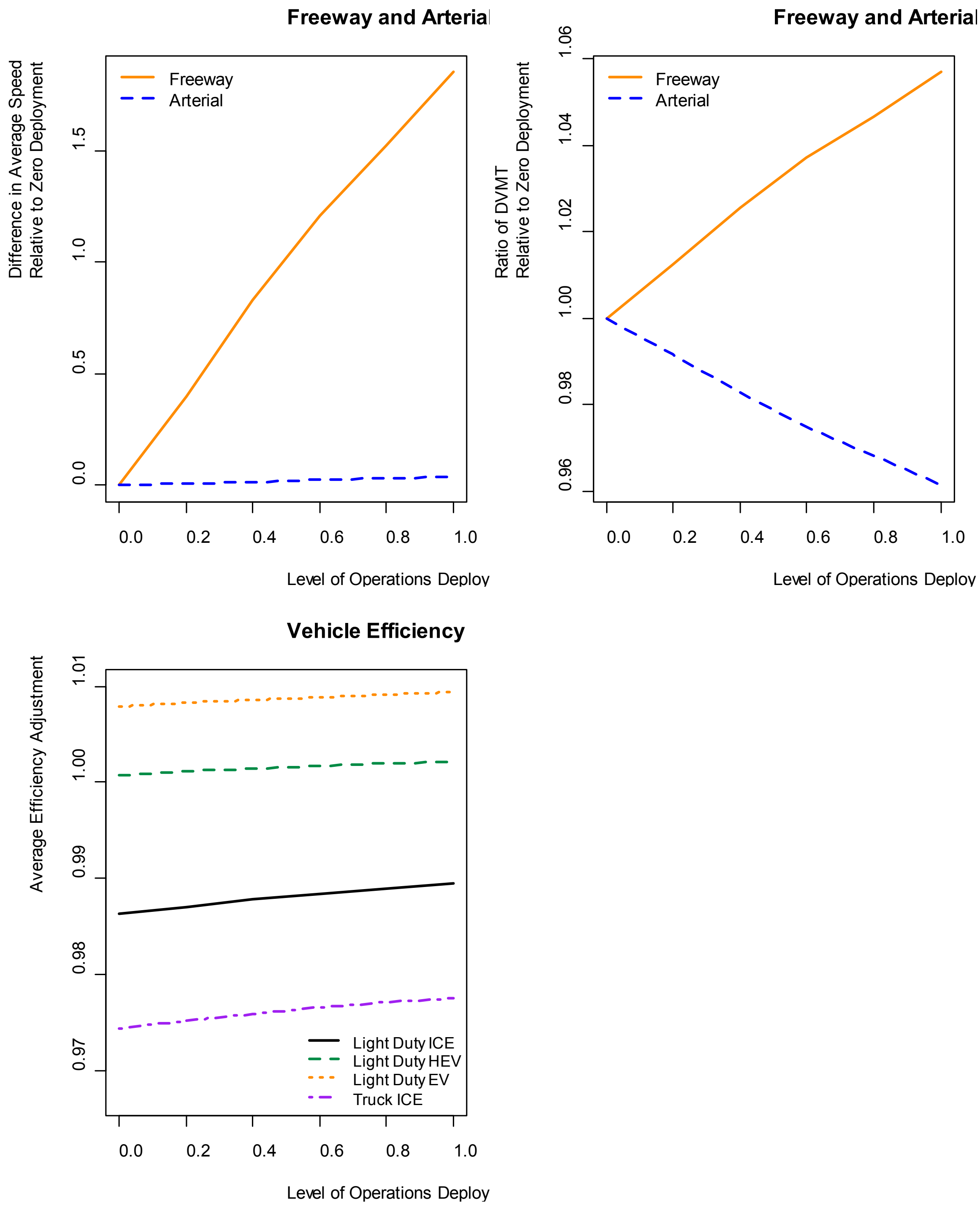


Figure 97. Modeled Effect of Arterial Operations Programs on Freeway and Arterial Speeds, DVMT and Vehicle Efficiency

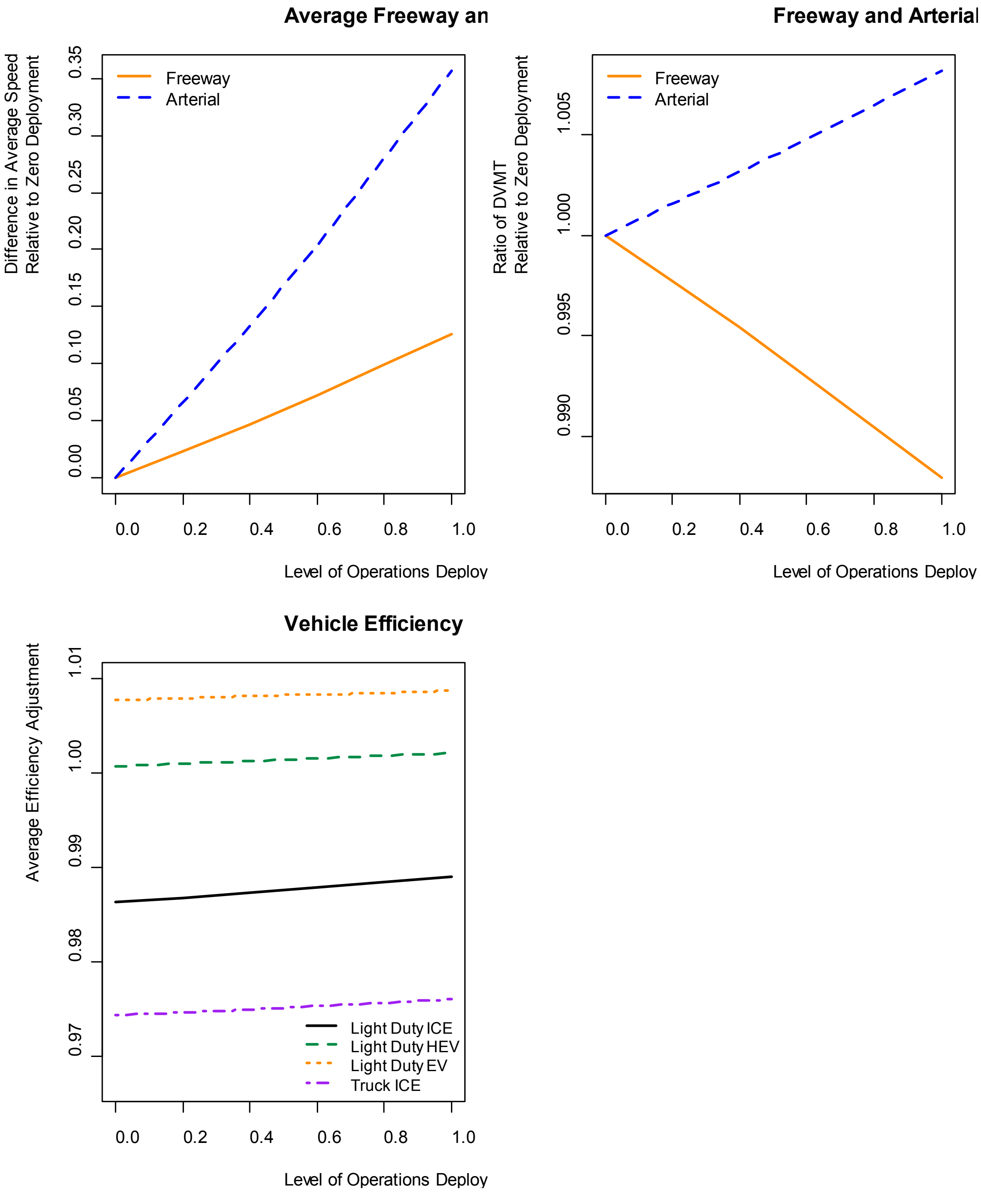
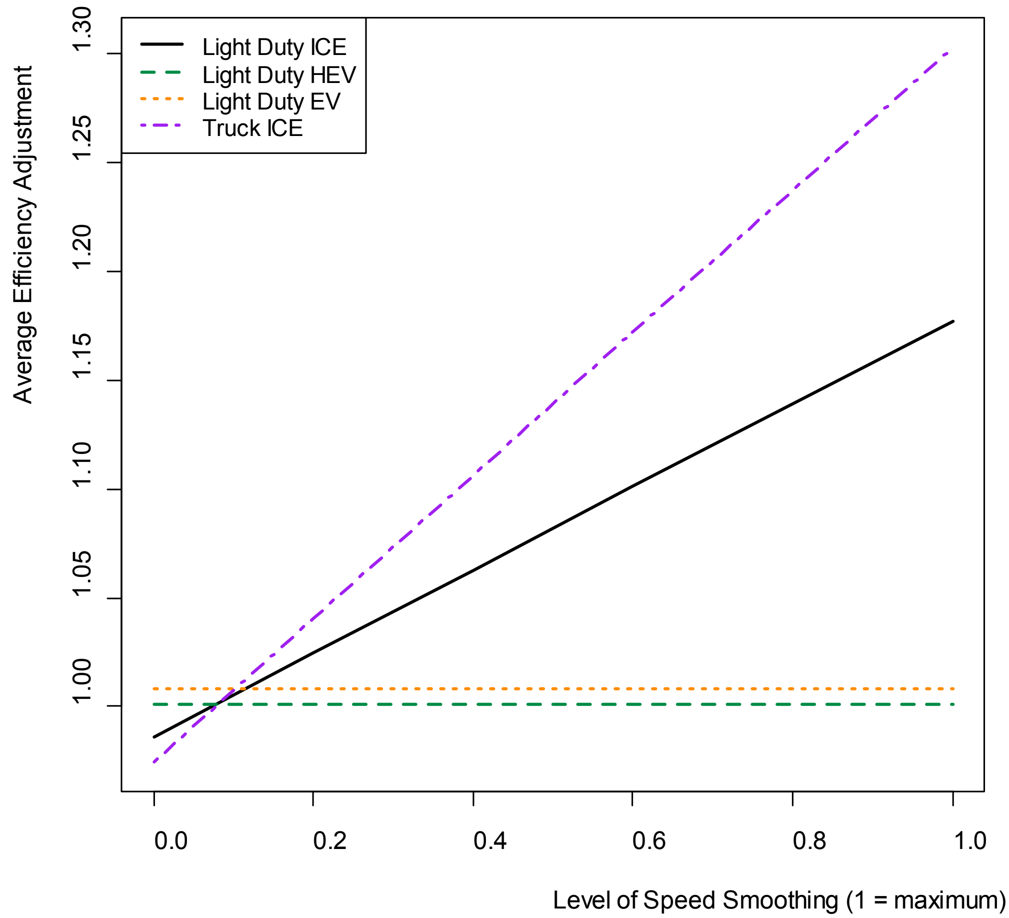


FIGURE 98. MODELED EFFECT OF TRAFFIC SMOOTHING ON ADJUSTMENTS TO AVERAGE VEHICLE EFFICIENCY



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Acronyms Used in This Report

ALD	Aggregate Land Development module of the Oregon Statewide Model
CARB	California Air Resources Board
CARBOB	Gasoline formulated to be blended with ethanol
CBO	U.S. Congressional Budget Office
CNG	Compressed natural gas
CO2	Carbon dioxide
CO2e	Carbon dioxide equivalent
DEQ	Oregon Department of Environmental Quality
DMV	ODOT Driver and Motor Vehicle Services Division
DVMT	Daily vehicle miles traveled
ECO	Employee commute options programs
EPA	U.S. Environmental Protection Agency
EV	Electric vehicle
FHWA	U.S. Federal Highway Administration
GHG	Greenhouse gas
GreenSTEP	**Green**house gas **S**tatewide **T**ransportation **E**missions **P**lanning model
HTHUR	Census tract level urban/rural continuum code used to classify area type in metropolitan areas.
IPF	Iterative proportional fitting process
JEMnR	Jointly estimated model in R (metropolitan area travel demand models)
LEV	Light-weight electric vehicle
LUSDR	**L**and **U**se **S**cenarios **D**evelope**R** model
MOVES	Motor Vehicle Emission Simulator model
MPG	Miles per gallon
MPH	Miles per hour
NHTS	National Household Travel Survey

NPTS	National Personal Travel Survey
ODOT	Oregon Department of Transportation
OSUM	**O**regon **S**mall **U**rban **M**odel (small urban area travel demand models)
ORS	Oregon Revised Statute
OTC	Oregon Transportation Commission
PAYD	Pay-as-you-drive
PHEV	Plug-in hybrid electric vehicle
PUMA	U.S. Census public use microsample area
PUMS	U.S. Census public use micro-sample data for Oregon
R	Open source programming language
RFG	Reformulated gasoline
SB1059	Oregon Senate Bill 1059
TDM	Transportation demand management
TPAU	ODOT Transportation Planning Analysis Unit
TRB	Transportation Research Board
ULSD	Ultra low sulfur diesel fuel
UMS	Urban Mobility Study
VMT	Vehicle miles traveled