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Energy and Emissions Reduction Policy Analysis Tool Model Documentation

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The FHWA acknowledges the development work carried out by Oregon Department of Transportation's Transportation Planning Analysis Unit on the GreenSTEP model, on which the FHWA Energy and Emissions Reduction Policy Analysis Tool is based. In addition, much of this model documentation was originally written by Transportation Planning Analysis Unit staff to accompany GreenSTEP and has been adapted by FHWA to document the FHWA Energy and Emissions Reduction Policy Analysis Tool.

EXECUTIVE SUMMARY

The FHWA Energy and Emissions Reduction Policy Analysis Tool (FHWA tool) is a screening tool to compare, contrast, and analyze various greenhouse gas (GHG) reduction policy scenarios for the transportation sector at a statewide level. The FHWA tool estimates GHG emissions from surface transportation, including fuel use (and electricity use for battery charging) by autos, light trucks, transit vehicles, and heavy trucks.

This FHWA Tool Model Documentation describes the model objectives, model design, the implementation platform, and the data sources used for model estimation. The documentation then describes the estimation of each of the model components. The documentation accompanies the FHWA Tool User's Guide, which describes how to set up and run the FHWA tool.

The FHWA tool is a policy analysis tool, and should not be used for specific project or plan evaluation. The FHWA tool complements tools such as EPA's MOVES (MOtor Vehicle Emission Simulator)[1] by providing rapid analysis of many scenarios that combine effects of various policy and transportation system changes. Users wishing to estimate detailed emissions for projects or corridors, or to evaluate detailed regional transportation impacts, should not rely on the FHWA tool. Such users should plan to use a project-level or regional travel demand model in conjunction with MOVES.

The FHWA tool is based on the Oregon Department of Transportation (ODOT) Transportation Planning Analysis Unit's (TPAU's) "GreenSTEP," a modeling tool to assess the effects of a large variety of policies and other factors on transportation sector GHG emissions. The FHWA tool was developed to address a wide range of factors, from changes in population demographics (age structure), land use characteristics, transportation supply, vehicle fleet characteristics, demand management programs, effects of pricing and congestion, through to the carbon intensity of fuels and electric power generation.

The FHWA tool is a system of disaggregate household-level models; the disaggregate nature of the models is intended to create a behaviorally consistent model. While the FHWA tool began as a sketch-planning model, the level of detail inherent in the current version has moved the FHWA tool out of that realm. Most of the FHWA tool 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.

[1] http://www.epa.gov/otaq/models/moves/index.htm

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1 INTRODUCTION

1.1 Introduction to the FHWA Tool

The FHWA Energy and Emissions Reduction Policy Analysis Tool (FHWA tool) is a screening tool to compare, contrast, and analyze various greenhouse has (GHG) reduction policy scenarios for the transportation sector at a statewide level. The FHWA tool estimates GHG emissions from surface transportation, including fuel use (and electricity use for battery charging) by autos, light trucks, transit vehicles, and heavy trucks.

Note: The FHWA tool is a policy analysis tool, and should not be used for specific project or plan evaluation. The FHWA tool complements tools such as EPA's MOVES (MOtor Vehicle Emission Simulator)[2] by providing rapid analysis of many scenarios that combine effects of various policy and transportation system changes. In order to provide quick response comparing many scenarios, the FHWA tool makes a number of simplifying assumptions (consistent with MOVES and with advanced regional travel demand modeling practice) that limit the detail and precision of its outputs. Users wishing to estimate detailed emissions for projects or corridors, or to evaluate detailed regional transportation impacts, should not rely on the FHWA tool. Such users should plan to use a project-level or regional travel demand model in conjunction with MOVES.

The FHWA tool is implemented in the free R data analysis language,[3] R provides a powerful, high-performance environment for data analysis that can be used interactively, as well as for scripted programs such as the FHWA tool. All code and data used in the FHWA tool analyses is freely available, and the code and data inputs can be reconfigured by technically adept users should that be necessary to support a specific analysis.

1.2 Model Documentation Structure

This FHWA Tool Model Documentation describes the model objectives, model design, the implementation platform, and the data sources used for model estimation. The documentation then describes the estimation of each of the model components. The documentation includes estimation results for the Oregon implementation of the FHWA tool. While many of the model components are estimated using national datasets, some models are specific to Oregon or the western Census region. This is noted in the discussion of the each model component. For applications of the FHWA tool in other states, these state- or region-specific models need to be re-estimated.

The documentation accompanies the FHWA Energy Tool User's Guide, which describes how to set up and run the FHWA tool. The user's guide also includes discussion of how to re-estimate the model components where that is necessary for new applications of the FHWA tool.

[2] http://www.epa.gov/otaq/models/moves/index.htm

[3] http://www.r-project.org

2 MODEL OBJECTIVES

The FHWA tool is based on the Oregon Department of Transportation (ODOT) Transportation Planning Analysis Unit's (TPAU's) "GreenSTEP," a modeling tool to assess the effects of a large variety of policies and other factors on transportation sector GHG emissions. The FHWA tool 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);
- Non-motorized vehicles (or two-wheeled electric vehicles) such as bicycles, electric bicycles, electric scooters, etc.;
- Pricing – fuel, vehicle miles traveled (VMT), parking;
- Demand management – employer-based and individual marketing programs;
- Car-sharing;
- Effects of congestion on fuel economy;
- Effects of highway incident management on fuel economy;
- Vehicle operation and maintenance – eco-driving, low rolling resistance tires, speed limits;
- Carbon intensity of fuels; and
- Carbon production from the electric power that is generated to run electric vehicles.

The FHWA tool addresses an entire state on a county basis to be responsive to regional differences. It distinguishes between households living in metropolitan, other urban, and rural areas to reflect the different characteristics of those areas in terms of density, urban form, transportation system characteristics, and transportation demand management (TDM) programs.

3 MODEL DESIGN

The FHWA tool is a system of disaggregate household-level models; the disaggregate nature of the models is intended to create a behaviorally consistent model. While the FHWA tool began as a sketch-planning model, the level of detail inherent in the current version has moved the FHWA tool out of that realm. Most of the FHWA tool operates at an individual household level where each household that the model synthesizes has individual attributes and where vehicle ownership and use is predicted on an individual synthesized 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 increasing shortened trips and increasing 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 EV and/or increases the proportion of household PHEV mileage that can be traveled on an electric charge. 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, in addition to fuel prices, 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.

The FHWA tool is designed to 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.

Figure 1 shows an overview of the FHWA tool model design (in two parts). The gray 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 which may be altered to represent different policies. The green boxes on the right side of the figure identify the models and methodologies that are 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

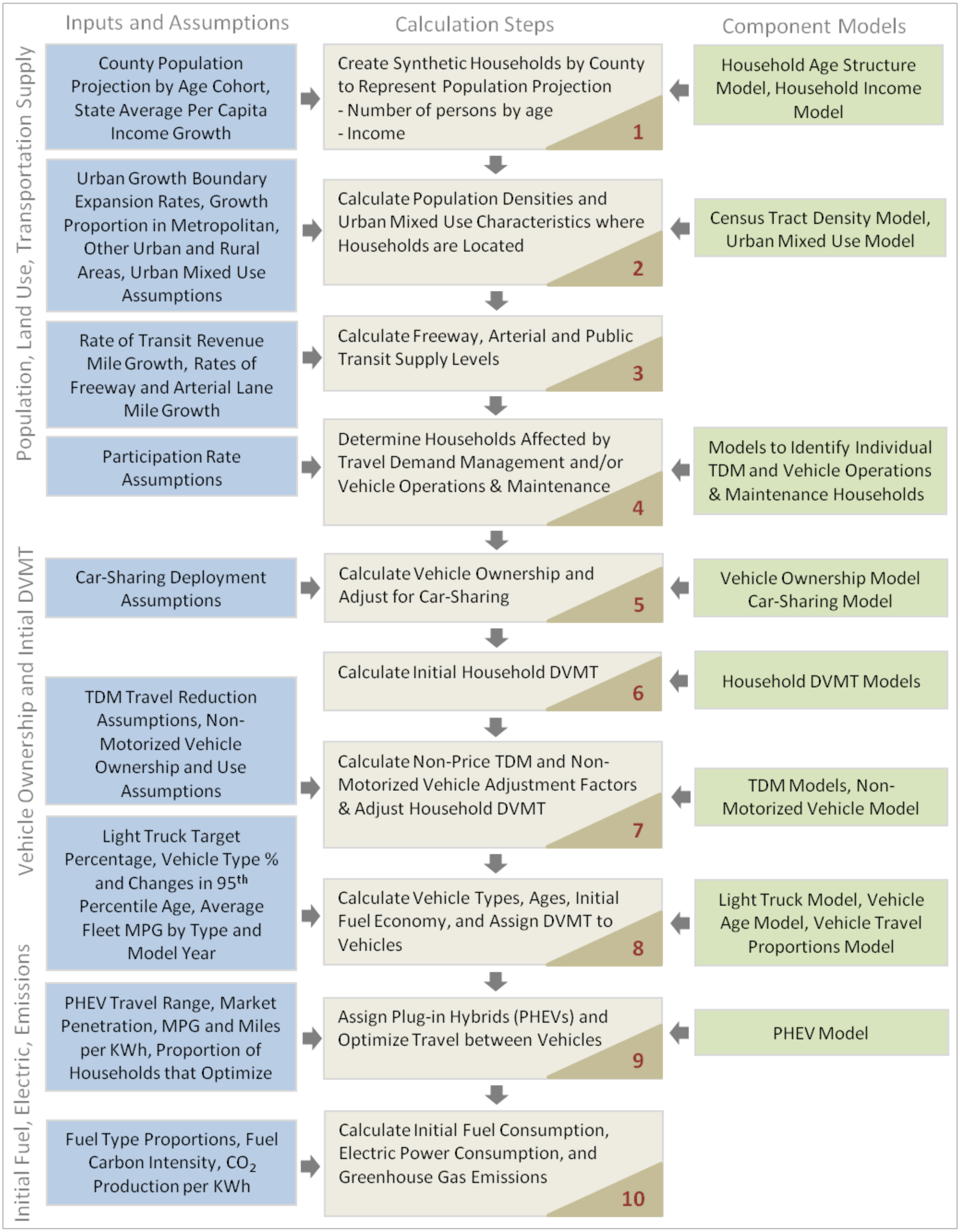
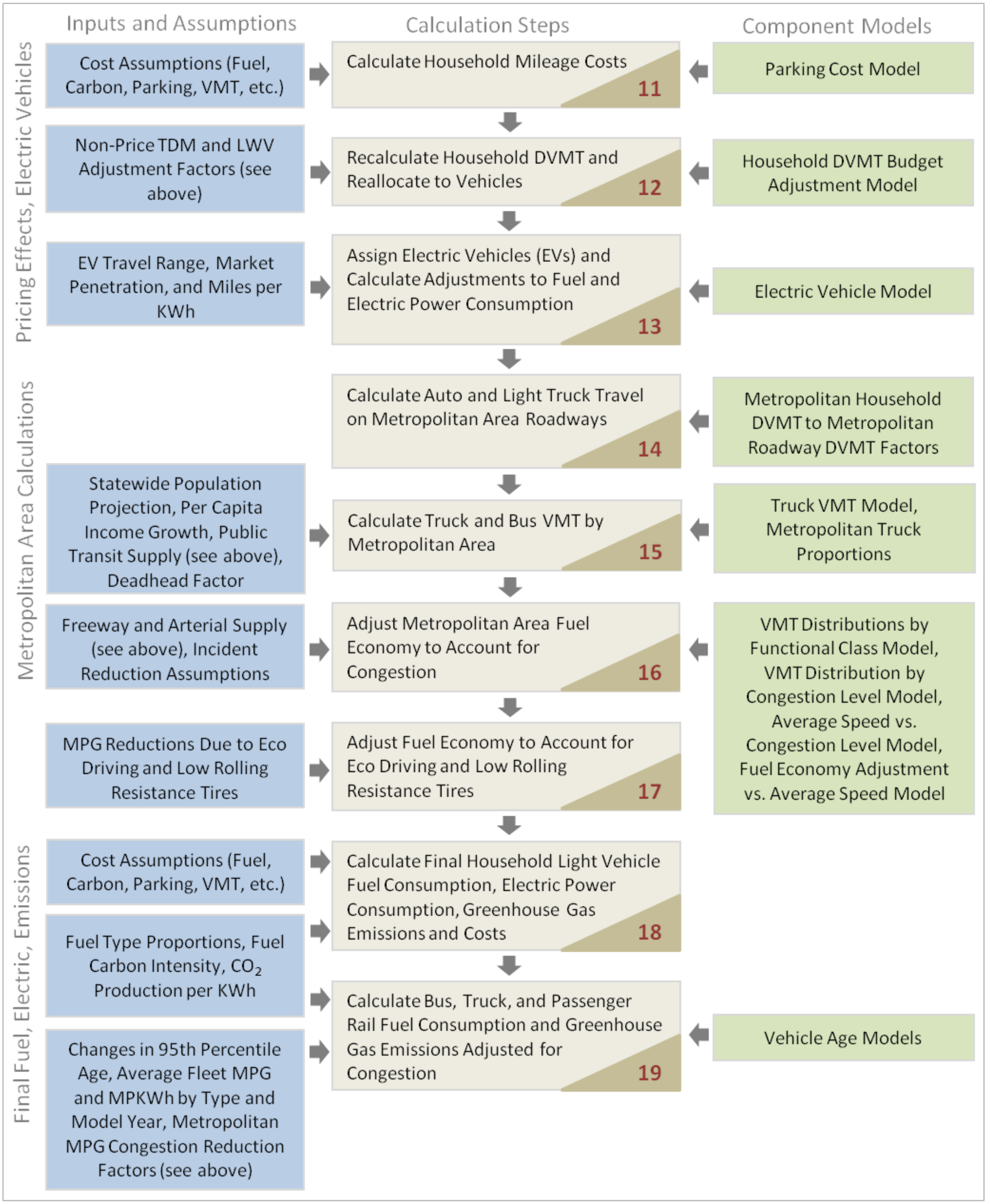


Figure 1: Design of Model for Estimating GHG from Passenger and Truck Travel (continued)



The following is an explanation of major steps in the model execution shown in the gray boxes in Figure 1.

1. ***Create Synthetic Households:*** A set of households is created for each forecast year that represents the likely household composition for each county, given the county-level forecast of persons by age. 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. Models were developed to estimate density and land use characteristics at a Census tract level based on more aggregate policy assumptions about metropolitan and other urban area characteristics.[4] Each household is assigned to a metropolitan, other urban, or rural development type in the county where it is located based on policy assumptions about the proportions of population growth that will occur in 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 household density distribution corresponding to the overall metropolitan area density. 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 they are 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.

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 as to how rapidly lane-miles are added relative to the addition of metropolitan population. For example, a value of one for freeways means that freeway lane-miles grow at the same rate as population grows. If population doubles, freeway lane-miles would double as well. For public transit, the inputs specify the growth in transit revenue miles relative to the base year. 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 being a participant or not in a number of travel demand management programs (e.g. employee commute options program, individualized marketing) and/or 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

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[4] The FHWA tool could be modified to operate at a metropolitan level with data being input for each Census tract.

ownership depends on the freeway supply, transit supply, and whether the household is located in an urban mixed-use area. Households are identified 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 based on 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 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 Non-Motorized 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 non-motorized vehicles travel for household DVMT. For the purposes of this documentation, non-motorized vehicles are bicycles, electric bicycles, and similar vehicles. The model predicts the potential amount of household DVMT that could be diverted to non-motorized vehicle travel using a model of the amount of household vehicle travel occurring in single-occupant vehicle (SOV) tours of less than various specified lengths. 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 non-motorized vehicle ownership rates, and assumptions about the proportion of the potential diverted vehicle travel that may be suitable for non-motorized vehicle travel. After the TDM and non-motorized factors have been calculated, they are applied to the initial household DVMT estimates to produce adjusted estimates.

8. ***Calculate Vehicle Types, Ages, Initial Fuel Economy, and Assign 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. Once vehicle ages have been determined, initial assignments of vehicle fuel economy are made based on input assumptions about average vehicle fuel economy by model year and vehicle type. Fuel economy is adjusted in later steps for vehicles identified as plug-in hybrid electric vehicles (PHEVs) and electric

vehicles (EVs) and to reflect the effects of congestion and vehicle operation and maintenance on fuel economy. Vehicles are assigned a proportion of the estimated household DVMT based on distributions of how annual household mileage is allocated among multiple vehicles. The distributions vary with the number of vehicles owned by the household. Average household DVMT is assigned to vehicles based on these proportions. This is done randomly without regard to vehicle characteristics. Later, in step #10, the allocations are optimized to maximize household fuel economy.

9. ***Assign Plug-in Hybrid Electric Vehicles (PHEVs) and Optimize Travel between Vehicles:*** Household vehicles are assigned as PHEVs based on input assumptions about market penetration by model year and vehicle type (auto vs. light truck) using a Monte Carlo process. Vehicles that are assigned as PHEVs will be used as the candidate pool in step #13 to identify EVs. Once PHEVs have 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 sorted by vehicle fuel economy, from most economical to least economical. It should be noted that this process does not change the sizes of the proportions of household VMT. It only changes which household vehicle is assigned with 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. ***Calculate Initial Fuel Consumption, Electric Power Consumption, and Greenhouse Gas Emissions:*** Fuel consumption is calculated for internal combustion engine (ICE) 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 electric power consumed and the assumed rates of greenhouse gas emissions per unit of power consumed.

11. ***Calculate Household Mileage Costs:*** Total variable vehicle costs (costs that vary based on vehicle usage) are calculated for each household. These costs include the cost of fuels and electric power. They may also include, depending on policy assumptions, carbon taxes, VMT taxes, pay-as-you-drive (PAYD) insurance rates, and parking charges. 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 with 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 at free parking lots. The model also estimates the proportion of non-work household trips and another model calculates daily parking charges for households paying for employment parking and other trip parking.

12. ***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 non-motorized vehicle use calculated in step #7 are applied.

13. ***Assign Electric Vehicles (EVs) and Calculate Adjustments to Fuel and Electric Power Consumption:*** Household vehicles are identified as candidates to be electric vehicles based on how their vehicle usage patterns compare with the average travel range of EVs for their vehicle model years. A vehicle is considered to be a candidate to be an EV only if the vehicle was identified as a PHEV in step #9 and if the EV 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 cost calculations in step #11 would be close to representing EV costs.

14. ***Calculate Auto and Light Truck Travel on Metropolitan Area Roadways:*** Since roadway congestion affects vehicle speeds and fuel economy, it is necessary to calculate roadway VMT in metropolitan areas. This is done by applying a factor calculated for the base year (2005) that is the ratio of urbanized area road auto and light truck DVMT calculated from Highway Performance Monitoring System (HPMS) data and the estimate of household DVMT of urbanized area households calculated by the FHWA tool. This ratio is calculated for each metropolitan area.

15. ***Calculate Truck and Bus DVMT and Assign Proportions to Metropolitan Areas:*** Statewide truck VMT is calculated based on changes in the total state income. As a default, a one-to-one relationship between state income growth and truck VMT growth is assumed. In other words, a doubling of total state income would result in a doubling of truck VMT. Portions of the statewide truck DVMT are assigned to metropolitan areas based on 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.

16. ***Adjust Metropolitan Area Fuel Economy to Account for Congestion:*** Auto and light truck DVMT, truck DVMT and bus DVMT in metropolitan areas are allocated to freeways, arterials and other roadways. Truck and bus DVMT are allocated based on mode-specific data derived from the HPMS data. Auto and light truck DVMT are allocated based on a combination of HPMS-derived factors and a model that is sensitive to the relative supplies of freeway and arterial lane miles. System-wide ratios of DVMT to lane-miles for freeways and arterials are used to allocate DVMT to congestion levels using congestion levels defined by the Texas Transportation Institute for the Urban Mobility Report. Each freeway and arterial congestion level is associated with an average trip speed for conditions that do and do not include highway incidents. Overall average speeds by congestion level are calculated based on input assumptions about the degree of incident management. Speed vs. fuel efficiency relationships for light vehicles, trucks, and buses are used to adjust the fleet fuel efficiency averages computed for each metropolitan area.

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.

18. ***Calculate Final Household Light Vehicle Fuel Consumption, Electric Power Consumption, Greenhouse Gas Emissions and Costs:*** Fuel consumption, electric power consumption, and greenhouse gas emissions are recalculated to reflect the adjusted fuel economy and power consumption.

19. ***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 #16.

3.1 Model Calculation Flow

The following calculation flow describes more specifically the mathematical processes that take place during a model run for a single year. The calculation flow is written as "pseudo code" in that it describes the process but simplifies significantly the R code used in the model; for clarity and readability the naming of objects has been simplified and certain model steps are described in text rather than mathematically.

The step numbering used refers to the major model steps shown in gray boxes in Figure 1. Input parameters and input files used are referenced. The locations in the calculation flow where the submodels described in this document are applied are noted, and differences between base and forecast years are indicated.

Certain naming conventions are used in the calculation flow:

- X (without a suffix) is a single variable (the values of which sometimes vary by run year)
- X.Ag is a table of data by vehicle model year (i.e. year that the vehicle was built)
- Similarly, other single suffixes indicate vectors of data by a categorical variable: .Ap = age of person, .Co = county, .Dt = development type, .Ft = fuel type, .Hh = household, .Ma = metropolitan area, .Rg = region, .Ty = vehicle type, .Ut = urban type, Yr. = run year
- Combinations of two suffixes indicate a two-dimensional table, e.g. MaFt is a table of data by metropolitan area and fuel type with specific values for each combination of metropolitan areas and fuel types.

1. CREATE SYNTHETIC HOUSEHOLDS

Population synthesis

Applies the createHhByAge process to create synthetic households for each county. Uses the HtProb.HtAp tabulation of household type and age of persons probabilities derived from PUMS data. Uses an iterative algorithm to create a balanced set of households.

List of households with ages Hsld.HhAp

Power-transformed per capita income by county

Applies calcCountyPowPerCapInc to calculate a power transformed per capita income by county, using the statewide per capita income for each forecast year, PerCapInc.Yr, from "per_cap_inc.csv", the regional income proportion, IncomeProp.Rg, from "regional_inc_prop.csv", and the region to county correspondence in "county_groups.csv". The power used in the model, pow = 0.4.

Regional per capita income ($/year)	PerCapInc.Rg = PerCapInc * IncomeProp.Rg
Per capita income by county ($/year)	PerCapInc.Co
Power transformed income	PowPerCapInc.Co = PerCapInc.Co ^ Pow

Household income

Applies the predictIncome calculation, which uses the IncomeModel linear regression model, to estimate household income.

Household income	Inc.Hh

Classifies income into groups, IncGrp.Hh, by selecting the group that Inc.Hh falls in, using income breaks at (0, 20000, 40000, 60000, 80000, 100000)

2. CALCULATE POPULATION DENSITIES AND OTHER LAND USE CHARACTERISTICS

Total population and households

Population by county	Pop.Co = sum(Hsld.HhAp)
Households by county	Hsld.Co = count(Hsld.HhAp)

Urban rural population proportions

Uses the urban rural population proportions in "urban_rural_pop_splits.csv", and the urban rural growth splits in "urban_rural_growth_splits.csv". For run years other than 2005 (the base year), the 2005 population is imported as BasePop.CoDt.

Population by dev. type (year <=2005)	UrbRurPop.CoDt = UrbRurPopProp.CoDt * Pop.Co
Population growth	PopGrowth.Co = Pop.Co - sum(BasePop.CoDt)
Population growth by dev. type	PopGrowth.CoDt = PopGrowth.Co * UrbRurGrowthSplit.CoDt
Population by dev. type (year > 2005)	UrbRurPop.CoDt = BasePop.CoDt + PopGrowth.CoDt

Urban growth boundary area

Uses the base year urban growth boundary (UGB) areas in "ugb_areas.csv" and the urban growth boundary growth rates in "ugb_area_growth_rates.csv".

UGB area (year <= 2005)	UgbAreas.CoUt = BaseUgbAreas.CoUt
Population growth rate by dev. type	PopGrowthRate.CoDt = PopGrowth.CoDt / BasePop.CoDt
UGB area (year > 2005)	UgbAreas.CoUt = (1 + PopGrowthRate.CoDt * UgbAreaGrowthRates.CoUt) * UgbAreas.CoUt

Urban density

Town density (people/sq mile)	TownDen.Co = UrbRurPop.CoDt(Town) / UgbAreas.CoUt(Town)
Metropolitan density (people/sq mile)	MetroDen.Co = UrbRurPop.CoDt(Metro)/UgbAreas.CoUt(Metro)

Rural density

Uses base year average rural densities by county in "ave_rural_pop_density.csv".

Rural density (<= 2005)	AveRuralDen.Co
Rural population	RuralPop.Co = UrbRurPop.CoDt(Rural)
Base year rural population	BaseRuralPop.Co = BasePop.CoDt(Rural)

Rural population growth	RuralPopGrowth.Co = RuralPop.Co – BaseRuralPop.Co
Rural density (>2005)	AveRuralDen.Co = AveRuralDen.Co * BaseRuralPop.Co / RuralPop.Co + 120 * RuralPopGrowth.Co / RuralPop.Co

Assign development types to households

Randomly sample households and assign to development types based on the probability of being in a particular development type, given by UrbRurPop.CoDt / sum(UrbRurPop.CoDt).

Development type	DevType.Hh

Density at household level

Applies the predictDensityUrban calculation, which uses the UbzDenModel_ models to assign each metropolitan household a population density drawn from a likely population density distribution corresponding to the overall metropolitan area density.

Density for metropolitan households	Den.Hh(Metro)
Density for households in towns	Den.Hh(Town) = TownDen.Co
Density for rural households	Den.Hh(Rural) = AveRuralDen.Co
Natural log of density	LogDen.Hh = log(Den.Hh)

Driving age population, elderly households, income summaries

Driving age population	DrvAgePop.Hh = Hsld.HhAp(-Age0to14)
Households having only elderly (>65)	OnlyElderly.Hh
Income by development type	Inc.CoDt = sum(Inc.Hh)
Base year income by dev. type	BaseInc.CoDt = Inc.CoDt (year = 2005)

3. CALCULATE FREEWAY, ARTERIAL, AND PUBLIC TRANSIT SUPPLY LEVELS

Metropolitan population growth proportion

Metropolitan pop. (forecast year)	Pop.Ma = sum(Pop.CoDt)
Base year metropolitan population	BasePop.Ma = sum(BasePop.CoDt)
Population change	PopChange.Ma = Pop.Ma / BasePop.Ma - 1

Per capita freeway lane miles

Uses "freeway_lane_miles.csv" which contains base year freeway lane miles by metropolitan area, and "fwy_art_growth.csv" which contains freeway lane mile growth rates relative to population growth by metropolitan area.

Per capita freeway lane miles (base)	FwyLnMiCap.Ma = 1000 * BaseFwyLnMi.Ma/Pop.Ma
Freeway lane mile growth	FwyLnMiGrowth.Ma = PopChange.Ma * FwyGrowth.Ma * BaseFwyLnMi.Ma
Freeway lane miles (future)	FwyLnMi.Ma = BaseFwyLnMi.Ma + FwyLnMiGrowth.Ma
Per capital freeway lane miles (future)	FwyLnMiCap.Ma = 1000 * FwyLnMi.Ma/Pop.Ma

Per capita arterial lane miles

Uses "arterial_lane_miles.csv" which contains base year arterial lane miles by metropolitan area, and "fwy_art_growth.csv" which contains arterial lane mile growth rates relative to population growth by metropolitan area.

Per capita arterial lane miles (base)	ArtLnMiCap.Ma = 1000 * BaseArtLnMi.Ma/Pop.Ma
Arterial lane mile growth	ArtLnMiGrowth.Ma = PopChange.Ma * ArtGrowth.Ma * BaseArtLnMi.Ma

Arterial lane miles (future)	ArtLnMi.Ma = BaseArtLnMi.Ma + ArtLnMiGrowth.Ma
Per capital arterial lane miles (future)	ArtLnMiCap.Ma = 1000 * ArtLnMi.Ma/Pop.Ma

Per capita transit revenue miles

Uses "transit_revenue_miles.csv" which contains per capita transit revenue miles by metropolitan area, and **"***transit_growth.csv" which contains transit revenue mile growth rates by metropolitan area.*

Transit revenue miles per capita (base)	TranRevMiCap.Ma = BaseTranRevMi.Ma
Bus revenue miles (base)	BusRevMi.Ma = BaseTranRevMi.Ma(Bus)*Pop.Ma
Rail revenue miles (base)	RailRevMi.Ma = BaseTranRevMi.Ma(Rail)*Pop.Ma
Transit rev. miles per capita (future)	TranRevMiCap.Ma = BaseTranRevMi.Ma*TranRevMiGrowth.Ma
Rail proportion	RailPropFactor.Ma = PctElectric.Ma / 100
Bus proportion	BusPropFactor = 1 – RailPropFactor.Ma
Rail revenue miles (future)	RailRevMi.Ma = TranRevMiCap.Ma*RailPropFactor.Ma*Pop.Ma
Bus revenue miles (future)	BusRevMi.Ma = TranRevMiCap.Ma*BusPropFactor.Ma*Pop.Ma

4. DETERMINE HOUSEHOLDS AFFECTED BY TRAVEL DEMAND MANAGEMENT AND/OR VEHICLE OPERATIONS AND MAINTENANCE PROGRAMS

Pay as you drive insurance households

Applies the idPayd calculation to select pay as you drive (PAYD) insurance households, which samples households randomly based on the proportion of PAYD households in "payd.csv".

PAYD households	IsPayd.Hh

Households participating in an employee commute options program

Applies the idEcoWorkers calculation to select metropolitan area households participating in an employee commute options program, based on "tdm.csv". Assumes a labor force participation rate = 0.65.

Prop. working age persons participating	PropWrkAgeEco.Ma = PropWrkEco.Ma * LabForcePartRate
Total working age persons	NumWrkAgePer.Ma = sum(DrvAgePop.Hh)
Num. working age persons participating	NumWrkAgeEco.Ma = PropWrkAgeEco.Ma*NumWrkAgePer.Ma

Identifies which persons are in an employee commute options program by randomly sampling the number of working age persons in NumWrkAgeEco.Ma, and calculates a variable at the household level.

Number of persons in program	NumEco.Hh

Households participating in individualized marketing

Applies the idImpHouseholds calculation to select metropolitan area households participating in individualized marketing, based on "tdm.csv". Assumes a density threshold = 4000 persons per square mile.

Numeric participation goal	NumImpHh.Ma = NumHh.Ma * ImpPropGoal.Ma

Candidate households (IsCandidate.Hh) live in areas with density greater than the density threshold. If there are fewer candidate households than the participation goal, all are identified as participating households; otherwise households are randomly selected until the participation goal is met.

Individualized marketing households	ImpHh.Hh

Eco-driver households

Applies the idEcoDriverHh calculation to select eco-driver households, which samples households randomly based on the proportion of eco-driver households in "eco_tire.csv".

Eco-driver households	IsEcoDriver.Hh

Low rolling resistance tire households
Applies the idLowRollTire calculation to select low rolling resistance tire households, which samples households randomly based on the proportion of low rolling resistance tire households in "eco_tire.csv".
Low rolling resistance tire households IsLowRollTire.Hh

5. CALCULATE VEHICLE OWNERSHIP AND ADJUST FOR CAR-SHARING

Vehicle ownership
Applies the predictVehOwn models to calculate vehicle ownership for each household. Binomial logit choice models are applied to estimate the probability that a household has zero, less than one, one, and more than one vehicle per driving age person; specific number of vehicles are then assigned to households in the less than one and more than one categories by drawing from the observed distribution of vehicle ownership in such households.
Number of household vehicles NumVeh.Hh

Car-share households
Applies the idCarshareHh calculation to select car-share households. Samples households randomly based on car-share probabilities calculated using the car-share rates in "carshare.csv".
Car-share households CarShare.Hh

Adjust vehicle ownership to account for car-sharing
Applies the adjCarshareOwn calculation to adjust car ownership (NumVeh.Hh) for car-sharing households by randomly sampling from distributions of car ownership.

6. CALCULATE INITIAL HOUSEHOLD DAILY VEHICLE MILES TRAVELED (DVMT)

Applies the calcAdjAveDvmt calculation, which predicts household DVMT using the predictAveDvmt regression models. Uses a base and future cost of 4 cents per mile so that budget constraints do not impinge on the amount of vehicle travel.
Initial household DVMT Dvmt.Hh

7. CALCULATE NON-PRICE TDM AND NON-MOTORIZED VEHICLE ADJUSTMENT FACTORS AND ADJUST HOUSEHOLD DVMT

TDM adjustment factor
Applies the adjDvmtEcoImp calculation to adjust DVMT for households participating in an employee commute options program and households participating in individualized marketing. Uses the reductions for each program (EcoRed.Ma, ImpRed.Ma) from "tdm.csv", and assumes that the proportion of work travel, PropWrkTrav, is 22%.
Adj. for employee commute options EcoAdjDvmt.Hh = Dvmt.Hh * (1 – EcoRed.Ma*PropWrkTrav)
Adj. for individualized marketing ImpAdjDvmt.Hh = Dvmt.Hh * (1 – ImpRed.Ma)
Calculation returns the adjusted DVMT that is the minimum for each household
DVMT adjusted for TDM programs TdmAdjDvmt.Hh = min(EcoAdjDvmt.Hh, ImpAdjDvmt.Hh)
TDM adjustment factor TdmAdjFactor.Hh = TdmAdjDvmt.Hh / Dvmt.Hh

Non-motorized vehicle adjustment factor

Applies the predictLightVehicles calculation to predict non-motorized vehicle ownership, using the linear regression models contained in LtVehOwnModels_ and "light_vehicles.csv".

Non-motorized vehicle ownership	LtVehOwn.Hh

Applies the calcLtVehDvmt calculation to predict non-motorized vehicle DVMT. This calculation uses the calcAveSovProp model to calculate SovDvmt.Hh, the amount of DVMT that is in single-occupant vehicles and within the distance threshold for possible non-motorized vehicle trips defined in "light_vehicles.csv". Converts some of the DVMT to non-motorized vehicle DVMT based on PropSuitable.Ma from "light_vehicles.csv".

Non-motorized veh. ownership ratio	LtVehPerDrvAgePop.Hh =LtVehOwn.Hh / DrvAgePop.Hh
Non-motorized vehicle DVMT	LtVehDvmt.Hh = SovDvmt.Hh * LtVehPerDrvAgePop.Hh * PropSuitable.Ma
Non-motorized veh. adj. factor	LtVehAdjFactor.Hh = LtVehDvmt.Hh / Dvmt.Hh

Overall DVMT adjustment

TDM and light veh. adjustment factor	TdmLtVehAdjFactor.Hh = TdmAdjFactor.Hh * LtVehAdjFactor.Hh
Adjusted DVMT	Dvmt.Hh = Dvmt.Hh * TdmLtVehAdjFactor.Hh

95th percentile and maximum DVMT

Applies the predictMaxDvmt calculation, which uses the DvmtLmModels_ regression models to estimate the 95th percentile and maximum DVMT for each household, based on each household's adjusted DVMT.

95th percentile DVMT	Dvmt95.Hh
Maximum DVMT	MaxDvmt.Hh

8. CALCULATE VEHICLE TYPES, AGES, INITIAL FUEL ECONOMY, AND ASSIGN DVMT TO VEHICLES

Vehicle type

Applies the predictLtTruckOwn calculation, which uses the LtTruckModels_ binomial logit choice models to identify household vehicles as either light trucks or autos, based on the light truck proportions by county, LtTruckProp.Co, in "lttruck_prop.csv".

Vehicle type	VehType.Hh

Vehicle age cumulative distributions

*Uses input data contained in VehProp_*

Cumulative age distributions by type	AgCumProp.AgTy
Distribution by age, income, and type	AgIgProp.AgIgTy

Vehicle age

Applies the calcVehiclesAges calculation to assign vehicle ages to the vehicles owned by each household. Adjusts the cumulative age distributions based on "age_adj.csv" using the adjustAgeDistribution calculation.

Adjusted age dist by type, income	VehAgeProp.AgIgTy
Num. vehicles by income, type	NumVeh.IgTy = sum(NumVeh.Hh, VehType.Hh, IncGrp.Hh)

Calculation samples vehicle ages randomly from the adjusted age distribution for each vehicle type and household income category until all of the draws for each income and vehicle combination in NumVeh.IgTy are made. Assigns a sampled age to each vehicle in each household.

Vehicle ages	VehAge.Hh

Vehicle fuel economy

Applies the assignFuelEconomy calculation to assign fuel economies to vehicles based on their vehicle type and vehicle age. Uses a table of vehicle fuel economies by vehicle type and vehicle age, VehMpg.AgTy, from "auto_lighttruck_mpg.csv".

Vehicle fuel economy (mpg)	VehMpg.Hh

Assign vehicle mileage to household vehicles

Applies the apportionDvmt calculation to randomly sample from DvmtProp_, a set of distributions of DVMT proportions for household vehicles.

DVMT proportions for each vehicle	DvmtProp.Hh
DVMT for each vehicle	VehDvmt.Hh = DvmtProp.Hh * Dvmt.Hh

9. ASSIGN PLUG-IN HYBRID ELECTRIC VEHICLES (PHEVS) AND OPTIMIZE TRAVEL BETWEEN VEHICLES

Assign PHEVs

Applies the assignPhev model to select which vehicles are PHEVs, adjusts fuel economy accordingly, and calculates mileage using hydrocarbons and electricity. Uses "phev_characteristics.csv", a table of auto and light truck PHEV ranges, vehicle fleet proportions, miles per kWh and fuel economy by vehicle model year.

PHEV range by year and vehicle type	PhevRange.AgTy
PHEV proportion	PhevProp.AgTy
PHEV electricity consumption	PhevMpkWh.AgTy
PHEV fuel economy	PhevMpg.AgTy

Select PHEVs (IsPhev.Hh) from household vehicles by random selection using PhevProp.AgTy as the threshold probability.

Adjust vehicle MPG to reflect PHEVs	VehMpg.Hh(IsPhev.Hh=1) = PhevMpg.AgTy
Vehicle electricity consumption	VehMpkwh.Hh(IsPhev=1) = PhevMpkwh.AgTy

Optimize allocation of DVMT to minimize fuel consumption

Optimizes allocation of DVMT between household vehicles to minimize fuel consumption for optimizing households based on the optimization factor in "optimize.csv". Selects households by randomly sampling up to the optimization factor. For selected households, vehicle DMVT proportions are assigned in order of fuel economy to minimize fuel consumption.

PHEV mileage using electricity and hydrocarbons

Applies the PhevPropModel_ regression models to calculate proportion of mileage using electricity.

Prop. PHEV mileage using electricity	ElecDvmtProp.Hh
Distances powered by electricity	EvVehDvmt.Hh = ElecDvmtProp.Hh * VehDvmt.Hh
Distances powered by hydrocarbons	HcVehDvmt.Hh = VehDvmt.Hh - EvVehDvmt.Hh

10. CALCULATE INITIAL FUEL CONSUMPTION, ELECTRIC POWER CONSUMPTION, AND GREENHOUSE GAS EMISSIONS

Average fuel CO_2 equivalent emissions per gallon

Applies the calcAveFuelCo2e model to calculate average $C0_2$ equivalent (CO_2e) emissions per gallon of fuel used. Uses fuel type proportions for autos (AutoLtTrkFuelProp.Ft) and light trucks (LtTrkFuelProp.Ft) contained in "auto_lighttruck_fuel.csv" , and CO_2e emissions by fuel type in grams per MJ (FuelCo2.Ft) contained in "fuel_co2.csv". MjPerGallon is an input parameter contained in global_values.txt.

Auto fuel carbon intensity (tonnes/gal)	AutoCo2e = AutoProp.Ft * FuelCo2.Ft *MjPerGallon / 1,000,000
Light truck fuel carbon intensity (t/gal)	LtTrkCo2e = LtTrkFuelProp.Ft * FuelCo2.Ft * MjPerGallon / 1,000,000

Average electricity CO_2e emissions per kWh

Applies the calcAveElectricCo2e model to calculate average CO_2e emissions per kWh of electricity used. Uses county-specific average pounds of CO_2e emissions per kWh of electricity consumed by the end user (PowerCo2.Co) contained in "power_co2.csv".

Average electricity CO2e (tonnes/kWh)	AveElectricCo2e.Co = PowerCo2.Co / 2,204.62262

Fuel use and emissions at a household level

Applies the calcVehFuelElecCo2 model to calculate fuel consumption and emissions at a household level.

For households <u>with vehicles</u>

Fuel consumption (gallons/day)	FuelGallons.Hh = HcVehDvmt.Hh / VehMpg.Hh
Emissions from fuel (tonnes/day)	FuelCo2e.Hh = FuelGallons.Hh * (AutoCo2e, LtTrkCo2e)
Electricity consumption (kWh/day)	ElecKwh.Hh = EvVehDvmt.Hh / VehMpkwh.Hh
Emissions from electricity (tonnes/day)	ElecCo2e.Hh = ElecKwh.Hh * AveElectricCo2e.Co

Totals in order to compute proportions and average rates

Total DVMT using fuel (miles/day)	TotHcDvmt = sum(HcVehDvmt.Hh)
Total DVMT using electricity (mile/day)	TotEvDvmt = sum(EvVehDvmt.Hh)
Total fuel consumption (gallons/day)	TotFuelGallons = sum(FuelGallons.Hh)
Total emissions from fuel (tonnes/day)	TotFuelCo2e = sum(FuelCo2e.Hh)
Total electricity cons. (kWh/day)	TotElecKwh = sum(ElecKwh.Hh)
Total emissions electricity (tonnes/day)	TotElecCo2e = sum(ElecCo2e.Hh)

For <u>zero-vehicle</u> households

Proportion DVMT using fuel	PropHcDvmt = TotHcDvmt / (TotHcDvmt + TotEvDvmt)
Average fuel cons. (gallons/mile)	AveGpm = TotFuelGallons / TotHcDvmt
Average fuel emissions (tonnes/mile)	AveFuelCo2eRate = TotFuelCo2e / TotHcDvmt
Average electricity cons. (kWh/mile)	AveKwhpm = TotElecKwh / TotEvDvmt
Av. electricity emissions (tonnes/mile)	AveElecCo2eRate = TotElecCo2e / TotEvDvmt
DVMT using fuel (miles/day)	HcVehDvmt.Hh = Dvmt.Hh * PropHcDvmt
DVMT using electricity (miles/day)	EvVehDvmt.Hh = Dvmt.Hh * (1 - PropHcDvmt)
Fuel consumption (gallons/day)	FuelGallons.Hh = HcVehDvmt.Hh * AveGpm
Emissions from fuel (tonnes/day)	FuelCo2e.Hh = HcVehDvmt.Hh * AveFuelCo2eRate
Electricity consumption (kWh/day)	ElecKwh.Hh = EvVehDvmt.Hh * AveKwhpm
Emissions from electricity (tonnes/day)	ElecCo2e.Hh = EvVehDvmt.Hh * AveElecCo2eRate

11. CALCULATE HOUSEHOLD MILEAGE COSTS

Paying parkers

Apply idPayingParkers calculation to identify paying parkers. Uses "parking.csv", a table of parking assumptions, and also assumes that the proportion of work travel, PropWrkTrav=0.22, the number of work days per year, WrkDaysPerYear=260, and a labor force participation rate, LabForcePartRate = 0.65.

Proportion work parking	PropWrkPkg.Ma
Proportion other parking	PropOthPkg.Ma = 1 – PropWrkPkg.Ma
Proportion charged for parking	PropChrgdPkg.Ma = PropWrkChrgd.Ma * PropWrkPkg.Ma + PropOthChrgd.Ma * PropOthPkg.Ma
Charged at work + other proportion	PropAvailPkg.Ma = PropWrkChrgd.Ma * PropWrkPkg.Ma + PropOthPkg.Ma
Proportion paying for work parking	PropWrkPay.Ma = PropWrkChrgd.Ma * PropChrgdPkg.Ma / PropAvailPkg.Ma
Prop. working age paying parkers	PropWrkAgePay.Ma = PropWrkPay.Ma * LabForcePartRate
Num. working age persons	NumWrkAgePer.Ma = sum(DrvAgePop.Hh)
Num. working age paying parkers	NumWrkAgePay.Ma = PropWrkAgePay.Ma*NumWrkAgePer.Ma
Num. that are cash-out-buy-back	NumCashOut.Ma = NumWrkAgePay.Ma * PropCashOut.Ma

Identifies which persons pay for parking and which persons get cash reimbursement for parking by randomly sampling persons until the total NumWrkAgePay.Ma and NumCashOut.Ma are met.

Num. persons who pay for parking	NumPayers.Hh
Num. persons who get reimbursement	NumCashOut.Hh

Parking costs

Applies calcParkCostAdj to calculate daily parking costs. Uses "parking.csv", a table of parking assumptions.

Daily work parking costs ($/day)	WrkPkgCost.Hh = NumPayers.Hh * PkgCost.Ma
Daily park. cost for non-work travel ($)	OthPkgCost.Hh = PkgCost.Ma * PropOthChrgd.Ma * (1 – PropWrkTrav)
Daily parking cost ($/day)	DailyPkgCost.Hh = WrkPkgCost.Hh + OthPkgCost.Hh
Parking cost per mile ($/mile)	PkgCostMile.Hh = 100 * DailyPkgCost.Hh/Dvmt.Hh
Cash out parking income ($/day)	CashOutIncAdj.Hh = NumCashOut.Hh * PkgCost.Ma * WrkDaysPerYear

Household travel costs

Applies the calcCosts model to calculate household travel costs using cost values in "costs.csv" (for fuel, electricity, VMT fees, Carbon taxes and Gas tax) and "payd.csv" for pay as you drive insurance costs.

All households

Total daily fuel cost ($/day)	FuelCost.Hh = FuelGallons.Hh * FuelCost
Gas tax cost ($/day)	GasTaxCost.Hh = FuelGallons.Hh * GasTax
Total daily power cost ($/day)	PowerCost.Hh = ElecKwh.Hh * KwhCost
Total daily carbon cost ($/day)	CarbonCost.Hh = (FuelCo2e.Hh + ElecCo2e.Hh) * CarbonCost
Total daily VMT cost ($/day)	VmtCost.Hh = Dvmt.Hh * VmtCost
Total daily PAYD cost ($/day)	PaydCost.Hh = Dvmt.Hh * Payd.Hh * PaydRate
Base vehicle cost ($/day)	BaseCost.Hh = FuelCost.Hh + GasTaxCost.Hh + PowerCost.Hh + CarbonCost.Hh + VmtCost.Hh
Total vehicle cost ($/day)	TotCost.Hh = BaseCost.Hh + PaydCost.Hh + DailyPkgCost.Hh

For households that have vehicles and DVMT

Average base cost per mile	AveBaseCostMile = mean(BaseCost.Hh / Dvmt.Hh)

For zero-vehicle households and households that have no DVMT

Total vehicle cost ($/day)	TotCost.Hh = Dvmt.Hh * 5 * AveBaseCostMile

All households

Average cost per mile	FutrCostPerMile.Hh = TotCost.Hh / Dvmt.Hh

For zero-vehicle households and households that have no DVMT

Average cost per mile	FutrCostPerMile.Hh = 5 * AveBaseCostMile

Reduce average cost per mile where it is out of the norm: for households where FutrCostPerMile.Hh > 95th percentile of FutrCostPerMile.Hh, set FutrCostPerMile.Hh = 95th percentile of FutrCostPerMile.Hh

12. RECALCULATE HOUSEHOLD DVMT AND REALLOCATE TO VEHICLES

Household DVMT with budget constraints

Applies the calcAdjAveDvmt calculation, which predicts household DVMT using the predictAveDvmt regression models. Uses costs calculated in Step #11 so that budget constraints do impinge on the amount of vehicle travel.

Previously calculated DVMT	PrevDvmt.Hh
Budget constrained household DVMT	Dvmt.Hh
DVMT adjusted for TDM participation	Dvmt.Hh = Dvmt.Hh * TdmLtVehAdjFactor.Hh

95^{th} percentile and maximum DVMT

Applies the predictMaxDvmt calculation, which uses the DvmtLmModels_ regression models to estimate the 95^{th} percentile and maximum DVMT for each household, based on each household's adjusted DVMT.

95^{th} percentile DVMT	Dvmt95.Hh
Maximum DVMT	MaxDvmt.Hh

Split adjusted DVMT among vehicles

DVMT adjustment factor	DvmtAdjFactor.Hh = Dvmt.Hh / PrevDvmt.Hh
Vehicle DVMT	VehDvmt.Hh = VehDvmt.Hh * DvmtAdjFactor.Hh
Electric powered DVMT	EvVehDvmt.Hh = EvVehDvmt.Hh * DvmtAdjFactor.Hh
Hydrocarbon powered DVMT	HcVehDvmt.Hh = HcVehDvmt.Hh * DvmtAdjFactor.Hh

13. ASSIGN ELECTRIC VEHICLES (EVS) AND CALCULATE ADJUSTMENTS TO FUEL AND ELECTRIC POWER CONSUMPTION

Applies the assignEv model to identify which of the candidate vehicles (the fleet of PHEVs) are EVs, and then calculates adjustments to fuel and electric power consumption. Uses "ev_characteristics.csv", a table of EV ranges, fleet proportions and electricity consumption per mile for autos and light trucks by vehicle model year.

EV range by year and vehicle type	EvRange.AgTy
EV proportion	EvProp.AgTy
Electricity consumption	EvMpkWh.AgTy
Candidate PHEVs	EvCandidate.Hh = Veh.Hh(VehDvmt95.Hh <= EvRange.AgTy and VehIsPhev.Hh = 1)

Select EVs (IsEv.Hh) from candidate vehicles by random selection from EvCandidate.Hh using EvProp.AgTy as the threshold probability.

EVs have no MPG	VehMpg.Hh(IsEv.Hh=1) = 0

All mileage is EV mileage	EvVehDvmt.Hh(IsEv.Hh=1) = EvVehDvmt.Hh+HcVehDvmt.Hh
No mileage uses hydrocarbon fuel	HcVehDvmt.Hh(IsEv.Hh=1) = 0
Electricity consumption	VehMpkwh.Hh(IsEv.Hh=1) = EvMpkWh.AgTy
EVs are no longer considered PHEVs	IsPhev.Hh(IsEv.Hh=1) = 0

14. CALCULATE AUTO AND LIGHT TRUCK TRAVEL ON METROPOLITAN AREA ROADWAYS

Model steps #14-16 are performed for metropolitan areas only as congestion is assumed not to occur outside metropolitan areas.

Uses a table of metropolitan area light vehicle DVMT totals, BaseLtVehDvmt.Ma, from the "LtVehDvmt" field in "mpo_base_dvmt_parm.csv"

DVMT by county, development type	Dvmt.CoDt = sum(Dvmt.Hh)
Household DVMT (miles/day)	HhDvmt.Ma = sum(Dvmt.CoDt)

Calculate factor in base year, apply saved factors in base and forecast years

HhDvmt to metropolitan road DVMT	LtVehDvmtFactor.Ma = BaseLtVehDvmt.Ma * 1000/HhDvmt.Ma
Metropolitan road DVMT (miles/day)	LtVehDvmt.Ma = HhDvmt.Ma * LtVehDvmtFactor.Ma

15. CALCULATE TRUCK AND BUS DVMT AND ASSIGN PROPORTIONS TO METROPOLITAN AREAS

Growth in total per capita income from base year

Total base year income ($)	BaseInc = sum(BaseInc.CoDt)
Forecast year income ($)	FutrInc = sum(Inc.CoDt)
Income growth factor	IncGrowth = FutrInc / BaseInc

Truck DVMT by metropolitan area

BaseTruckVmt and TruckVmtGrowthMultiplier are input parameters contained in global_values.txt. PropTruckDvmt.Ma is a table of the proportion of truck DVMT that occurs in each metropolitan area, from the "PropTruckDvmt" field in "mpo_base_dvmt_parm.csv".

Truck DVMT (miles/day)	TruckDvmt = IncGrowth * TruckVmtGrowthMultiplier * BaseTruckVmt / 365
Truck DVMT by metro area (miles/day)	TruckDvmt.Ma = TruckDvmt *PropTruckDvmt.Ma

Bus DVMT by metropolitan area

TranAdjFactor is an input parameter contained in global_values.txt that accounts for deadheading to convert transit revenue miles to vehicle miles

Bus DVMT by metro area (miles/day)	BusDvmt.Ma = BusRevMi.Ma * TranAdjFactor / 365

16. ADJUST METROPOLITAN AREA FUEL ECONOMY TO ACCOUNT FOR CONGESTION

Applies the calcCongestion model to calculate the fuel economy adjustment, travel times, travel speeds, and travel delay due to congestion. Uses several inputs:

IncdReduc.Ma = Incident reduction factors from "metro_incident_reduction.csv"
FwyArtProp.Ma = Freeway/arterial prop. for light vehicles from "mpo_base_dvmt_parm.csv"
BusVmtSplit.MaFc = Functional class proportions for bus from "truck_bus_fc_dvmt_split.csv"
TruckVmtSplit.MaFc = Functional class proportions for truck from "truck_bus_fc_dvmt_split.csv"

Split DVMT between functional classes (freeways, arterials, and other roads)

Lt. veh. freeway and arterial DVMT	LtVehFwyArtDvmt.Ma = LtVehDvmt.Ma * FwyArtProp.Ma
Freeway to arterial lane mile ratio	LnMiRatio.Ma = FwyLnMiCap.Ma / ArtLnMiCap.Ma

Applies the DvmtRatio linear regression model (CongModel_$DvmtRatio) to calculate the ratio of freeway to arterial DVMT, FwyArtDvmtRatio.Ma

Lt. veh. freeway DVMT (miles/day)	LtVehFwyDvmt.Ma = LtVehFwyArtDvmt.Ma * FwyArtDvmtRatio.Ma / (1 + FwyArtDvmtRatio.Ma)
Lt. veh. arterial DVMT (miles/day)	LtVehArtDvmt.Ma = LtVehFwyArtDvmt.Ma–LtVehFwyDvmt.Ma
Lt. veh. other DVMT (miles/day)	LtVehOthDvmt.Ma = LtVehDvmt.Ma – LtVehFwyArtDvmt.Ma
Truck Dvmt by functional class (mi/day)	TruckDvmt.MaFc = TruckDvmt.Ma * TruckVmtSplit.MaFc
Bus Dvmt by functional class (mi/day)	BusDvmt.MaFc = BusDvmt.Ma * BusVmtSplit.MaFc

Freeway DVMT proportions by congestion level (None, Moderate, Heavy, Severe, Extreme)

Total freeway DVMT	FwyDvmt.Ma = LtVehFwyDvmt.Ma + TruckDvmt.MaFc(Fwy) + BusDvmt.MaFc(Fwy)
Freeway demand level	FwyDemandLvl.Ma = FwyDvmt.Ma /(FwyLnMiCap.Ma * Pop.Ma / 1000)

Applies the freeway congestion linear regression models (CongModel_$Fwy) to calculate the percentage of DVMT in the no, heavy, severe, and extreme categories. The moderate congestion level is calculated as 100 – the sum of the other 4 categories, to complete FwyDvmtPct.MaCl

Arterial DVMT proportions by congestion level (None, Moderate, Heavy, Severe, Extreme)

Total arterial DMVT	ArtDvmt.Ma = LtVehArtDvmt.Ma + TruckDvmt.MaFc(Art) + BusDvmt.MaFc(Art)
Arterial demand level	ArtDemandLvl.Ma = ArtDvmt.Ma /(ArtLnMiCap.Ma * Pop.Ma / 1000)

Applies the arterial congestion linear regression models (CongModel_$Art) to calculate the percentage of DVMT in the no, heavy, severe, and extreme categories. The moderate congestion level is calculated as 100 – the sum of the other 4 categories, to complete ArtDvmtPct.MaCl

DVMT by vehicle type, functional class and congestion level

All DVMT on “other” functional class roads is assumed to fall in the no congestion category

Lt. veh. freeway DVMT (miles/day)	LtVehDvmt.MaClFc(Fwy) = LtVehFwyDvmt.Ma * FwyDvmtPct.MaCl / 100
Lt. veh. arterial DVMT (miles/day)	LtVehDvmt.MaClFc(Art) = LtVehArtDvmt.Ma * ArtDvmtPct.MaCl / 100
Truck freeway DVMT (miles/day)	TruckDvmt.MaClFc(Fwy) = TruckDvmt.MaFc(Fwy) * FwyDvmtPct.MaCl / 100
Truck arterial DVMT (miles/day)	TruckDvmt.MaClFc(Art) = TruckDvmt.MaFc(Art) * ArtDvmtPct.MaCl / 100
Bus freeway DVMT (miles/day)	BusDvmt.MaClFc(Fwy) = BusDvmt.MaFc(Fwy) * FwyDvmtPct.MaCl / 100
Bus arterial DVMT (miles/day)	BusDvmt.MaClFc(Art) = BusDvmt.MaFc(Art) * ArtDvmtPct.MaCl / 100

Congested speeds by congestion level and functional class

Selects the freeway and arterial speeds for each congestion level with and without highway incidents from speed tables (CongModel_$Speeds) to fill FwySpeed.ClCc and ArtSpeed.ClCc.

Average freeway speeds (mph) FwySpeed.MaCl = FwySpeed.ClCc * IncdReduc.Ma
Average arterial speeds (mph) ArtSpeed.MaCl = ArtSpeed.ClCc * IncdReduc.Ma
Since no congestion is assumed on "other" functional class roads, OthSpeed.MaCl is filled with freeflow speed for "other" functional class from CongModel_$FreeFlowSpeed.Fc.
Congested speeds by functional class CongSpeed.MaClFc

Normal bus operating speeds (CongModel_$BusSpeeds.Fc) on arterials are lower than freeflow speed, but are likely to be similar to (and should not exceed) congested speeds.
Bus speeds on freeways (mph) BusFwySpeed.MaCl = FwySpeed.MaCl
Bus speeds on arterials (mph) BusArtSpeed.MaCl = min(ArtSpeed.MaCl, BusSpeeds.Fc(Art))
Bus speeds on other roads (mph) BusOthSpeed.MaCl = BusSpeeds.Fc(Oth)
Bus speeds by functional class BusCongSpeed.MaClFc

Light vehicle, truck, and bus MPG adjustments
Selects the light vehicle, truck, and bus freeway, arterial, and other road MPG adjustment values for the congested speeds from the adjustment tables for each congestion level and functional class (CongModel_$FwySpdMpgAdj, CongModel_$ArtSpdMpgAdj, and CongModel_$OtherSpdMpgAdj). The tables are in 5 mph increments, so the adjustment is interpolated to match the values of the congested speed. Fills LtVehMpgAdj.MaClFc, TruckMpgAdj.MaClFc, and BusMpgAdj.MaClFc.
Lt. veh. MPG adjustment LtVehMpgAdj.Ma = sum(LtVehMpgAdj.MaClFc * LtVehDvmt.MaClFc) / sum(LtVehDvmt.MaClFc)
Truck MPG adjustment TruckMpgAdj.Ma = sum(TruckMpgAdj.MaClFc * TruckDvmt.MaClFc) / sum(TruckDvmt.MaClFc)
Bus MPG adjustment BusMpgAdj.Ma = sum(BusMpgAdj.MaClFc * BusDvmt.MaClFc) / sum(BusDvmt.MaClFc)

Total vehicle travel time by vehicle type
Lt. veh. travel time (hours) LtVehHr.Ma = sum(LtVehDvmt.MaClFc / CongSpeed.MaClFc)
Truck travel time (hours) TruckHr.Ma = sum(TruckDvmt.MaClFc / CongSpeed.MaClFc)
Bus travel time (hours) BusHr.Ma = sum(BusDvmt.MaClFc / BusCongSpeed.ClFc)

Average speed by vehicle type
Lt. veh. average speed (mph) LtVehAveSpeed.Ma = sum(LtVehDvmt.MaClFc) / LtVehHr.Ma
Truck average speed (mph) TruckAveSpeed.Ma = sum(TruckDvmt.MaClFc) / TruckHr.Ma
Bus average speed (mph) BusAveSpeed.Ma = sum(BusDvmt.MaClFc) / BusHr.Ma

Vehicle delay by vehicle type
Uses the tables of freeflow travel times by facility type in CongModel_$FreeFlowSpeed.Fc (same for light vehicles and trucks) and CongModel_$BusSpeeds.Fc (for buses).
Lt. veh. freeflow travel time (hours) LtVehFfHr.Ma = sum(LtVehDvmt.MaClFc) / FreeFlowSpeed.Fc
Truck freeflow travel time (hours) TruckFfHr.Ma = sum(TruckDvmt.MaClFc) / FreeFlowSpeed.Fc
Bus freeflow travel time (hours) BusFfHr.Ma = sum(BusDvmt.MaClFc) / BusSpeeds.Fc
Lt. veh hours of delay (hours) LtVehDelayVehHr.Ma <- LtVehHr.Ma - LtVehFfVehHr.Ma
Truck hours of delay (hours) TruckDelayVehHr.Ma <- TruckHr.Ma - TruckFfVehHr.Ma
Truck hours of delay (hours) TruckDelayVehHr.Ma <- TruckHr.Ma - TruckFfVehHr.Ma
Adjust the light vehicle fuel economy due to congestion
Assumes that the household VMT outside metropolitan area is uncongested.

Fuel economy adjustment	HhMpgAdj.Ma = (LtVehMpgAdj.Ma * LtVehDvmtFactor.Ma) + (1 - LtVehDvmtFactor.Ma)
Adjusted fuel economy (mpg)	VehMpg.Hh = VehMpg.Hh * HhMpgAdj.Ma

17. ADJUST FUEL ECONOMY TO ACCOUNT FOR ECO-DRIVING AND LOW ROLLING RESISTANCE TIRES

Applies the adjEcoTire model to adjust the vehicle fuel economy and energy efficiency for households that eco-drive and for vehicles that have low rolling resistance tires. Uses "eco_tire.csv" where:

Eco-driving MPG improvement	EcoMpgImp
Eco-driving electricity use reduction	EcoMpkwhImp
Low rolling resistance tires MPG imp.	TireMpgImp
Low rolling resistance tires elec. red.	TireMpkwhImp

Eco-driving fuel economy adjustment	EcoMpgAdj.Hh = 1 + IsEcoDriver.Hh * EcoMpgImp
Eco-driving energy efficiency adj.	EcoMpkwhAdj.Hh = 1 + IsEcoDriver.Hh * EcoMpkwhImp
Tires fuel economy adjustment	TireMpgAdj.Hh = 1 + IsLowRollTire.Hh * TireMpgImp
Tires fuel energy efficiency adjustment	TireMpkwhAdj.Hh = 1 + IsLowRollTire.Hh * TireMpkwhImp
Adjusted vehicle fuel economy (mpg)	VehMpg.Hh = VehMpg.Hh * EcoMpgAdj.Hh * TireMpgAdj.Hh
Adj. vehicle energy efficiency (mpkWh)	VehMpkwh.Hh = VehMpkwh.Hh * EcoMpkwhAdj.Hh * TireMpkwhAdj.Hh

18. CALCULATE FINAL HOUSEHOLD LIGHT VEHICLE FUEL CONSUMPTION, ELECTRIC POWER CONSUMPTION, GREENHOUSE GAS EMISSIONS, AND COSTS

Average fuel CO_2e per gallon

Applies the calcAveFuelCo2e model to calculate average $C0_2$e emissions per gallon of fuel used. Uses fuel type proportions for auto (AutoLtTrkFuelProp.Ft) and light trucks (LtTrkFuelProp.Ft) contained in "auto_lighttruck_fuel.csv" , and CO_2e emissions by fuel type in grams per MJ (FuelCo2.Ft) contained in "fuel_co2.csv". MjPerGallon is an input parameter contained in global_values.txt.

Auto fuel carbon intensity (tonnes/gal)	AutoCo2e = AutoProp.Ft * FuelCo2.Ft *MjPerGallon / 1,000,000
Light truck fuel carbon intensity (t/gal)	LtTrkCo2e = LtTrkFuelProp.Ft * FuelCo2.Ft * MjPerGallon / 1,000,000

Average electricity CO_2e per kWh

Applies the calcAveElectricCo2e model to calculate average CO_2e emissions per kWh of electricity used. Uses county specific average pounds of CO_2e emissions per kWh of electricity consumed by the end user (PowerCo2.Co) contained in "power_co2.csv".

Average electricity CO2e (tonnes/kWh)	AveElectricCo2e.Co = PowerCo2.Co / 2,204.62262

Fuel use and emissions at a household level

Applies the calcVehFuelElecCo2 model to calculate fuel consumption and emissions at a household level.

For households <u>with vehicles</u>

Fuel consumption (gallons/day)	FuelGallons.Hh = HcVehDvmt.Hh / VehMpg.Hh
Emissions from fuel (tonnes/day)	FuelCo2e.Hh = FuelGallons.Hh * (AutoCo2e, LtTrkCo2e)
Electricity consumption (kWh/day)	ElecKwh.Hh = EvVehDvmt.Hh / VehMpkwh.Hh
Emissions from electricity (tonnes/day)	ElecCo2e.Hh = ElecKwh.Hh * AveElectricCo2e.Co

Totals in order to compute proportions and average rates

Total DVMT using fuel (miles/day)	TotHcDvmt = sum(HcVehDvmt.Hh)
Total DVMT using electricity (mile/day)	TotEvDvmt = sum(EvVehDvmt.Hh)
Total fuel consumption (gallons/day)	TotFuelGallons = sum(FuelGallons.Hh)
Total emissions from fuel (tonnes/day)	TotFuelCo2e = sum(FuelCo2e.Hh)
Total electricity cons. (kWh/day)	TotElecKwh = sum(ElecKwh.Hh)
Total emissions electricity (tonnes/day)	TotElecCo2e = sum(ElecCo2e.Hh)

For <u>zero-vehicle</u> households

Proportion DVMT using fuel	PropHcDvmt = TotHcDvmt / (TotHcDvmt + TotEvDvmt)
Average fuel cons. (gallons/mile)	AveGpm = TotFuelGallons / TotHcDvmt
Average fuel emissions (tonnes/mile)	AveFuelCo2eRate = TotFuelCo2e / TotHcDvmt
Average electricity cons. (kWh/mile)	AveKwhpm = TotElecKwh / TotEvDvmt
Av. electricity emissions (tonnes/mile)	AveElecCo2eRate = TotElecCo2e / TotEvDvmt
DVMT using fuel (miles/day)	HcVehDvmt.Hh = Dvmt.Hh * PropHcDvmt
DVMT using electricity	EvVehDvmt.Hh = Dvmt.Hh * (1 - PropHcDvmt)
Fuel consumption (gallons/day)	FuelGallons.Hh = HcVehDvmt.Hh * AveGpm
Emissions from fuel (tonnes/day)	FuelCo2e.Hh = HcVehDvmt.Hh * AveFuelCo2eRate
Electricity consumption (kWh/day)	ElecKwh.Hh = EvVehDvmt.Hh * AveKwhpm
Emissions from electricity (tonnes/day)	ElecCo2e.Hh = EvVehDvmt.Hh * AveElecCo2eRate

Household travel costs

Applies the calcCosts model to calculate household travel costs using cost values in "costs.csv" (for fuel, electricity, VMT fees,carbon taxes and gas tax) and "payd.csv" for pay as you drive insurance costs.

All households

Total daily fuel cost ($/day)	FuelCost.Hh = FuelGallons.Hh * FuelCost
Gas tax cost ($/day)	GasTaxCost.Hh = FuelGallons.Hh * GasTax
Total daily power cost ($/day)	PowerCost.Hh = ElecKwh.Hh * KwhCost
Total daily carbon cost ($/day)	CarbonCost.Hh = (FuelCo2e.Hh + ElecCo2e.Hh) * CarbonCost
Total daily VMT cost ($/day)	VmtCost.Hh = Dvmt.Hh * VmtCost
Total daily PAYD cost ($/day)	PaydCost.Hh = Dvmt.Hh * Payd.Hh * PaydRate
Base vehicle cost ($/day)	BaseCost.Hh = FuelCost.Hh + GasTaxCost.Hh + PowerCost.Hh + CarbonCost.Hh + VmtCost.Hh
Total vehicle cost ($/day)	TotCost.Hh = BaseCost.Hh + PaydCost.Hh + DailyPkgCost.Hh

For households that <u>have vehicles and DVMT</u>

Average base cost per mile	AveBaseCostMile = mean(BaseCost.Hh / Dvmt.Hh)

For <u>zero-vehicle</u> households and households that <u>have no DVMT</u>

Total vehicle cost ($/day)	TotCost.Hh = Dvmt.Hh * 5 * AveBaseCostMile

All households

Average cost per mile	FutrCostPerMile.Hh = TotCost.Hh / Dvmt.Hh

For <u>zero-vehicle</u> households and households that <u>have no DVMT</u>

Average cost per mile	FutrCostPerMile.Hh = 5 * AveBaseCostMile

Reduce average cost per mile where it is out of the norm: for households where FutrCostPerMile.Hh > 95^{th} percentile of FutrCostPerMile.Hh, set FutrCostPerMile.Hh = 95^{th} percentile of FutrCostPerMile.Hh

Average household DVMT in short SOV tours

Applies the calcShortSovVmtProp and calcAveSovProp models to calculate the proportion of DVMT in 2-mile or shorter SOV tours and the proportion of DVMT in 5-mile or shorter SOV tours.

19. CALCULATE BUS, TRUCK, AND PASSENGER RAIL FUEL CONSUMPTION AND GREENHOUSE GAS EMISSIONS ADJUSTED FOR CONGESTION

Truck and bus age cumulative distributions

Uses input data contained in TruckBusAgeDist.AgTy.

Truck age cumulative distribution	TruckAgeDist.Ag
Bus age cumulative distribution	BusAgeDist.Ag

Adjusted truck and bus age distributions

Applies the adjustHvyVehAgeDistribution model to adjust the truck and bus age cumulative distributions based on "age_adj.csv" and to convert them to regular distributions.

Truck age distribution	TruckAgProp.Ag = TruckAgeDist.Ag, TruckAgeAdj
Bus age distribution	BusAgProp.Ag = BusAgeDist.Ag, BusAgeAdj

Truck and bus fuel economy

Applies the assignHvyVehFuelEconomy model to calculate the weighted average fuel economy using the vehicle age distribution and the vehicle fuel economy for each year, HvyVehMpgMpk.Ag, from "hvy_veh_mpg_mpk.csv".

Truck fuel economy (mpg)	TruckMpg = sum(TruckAgProp.Ag *HvyVehMpgMpk.Ag)
Bus fuel economy (mpg)	BusMpg = sum(BusAgProp.Ag * HvyVehMpgMpk.Ag)

Adjust truck and bus fuel economy to account for congestion

Adjusted truck fuel economy (mpg)	TruckMpg.Ma = TruckMpg * TruckMpgAdj.Ma
Adjusted bus fuel economy (mpg)	BusMpg.Ma = BusMpg * BusMpgAdj.Ma

Truck fuel consumption by fuel type

TruckFuelProp.Ft is a table of proportions of fuel types used by trucks, in "heavy_truck_fuel.csv". The fuel types are ULSD, biodiesel, gasoline, ethanol, and CNG.

Overall fuel consumption (gallons/day)	TruckFuel.Ma = TruckDvmt.Ma / TruckMpg.Ma
Fuel consumption by type (gallons/day)	TruckFuel.MaFt = TruckFuel.Ma * TruckFuelProp.Ft

Bus fuel consumption by fuel type

BusFuelProp.MaFt is a table of proportions of fuel types used by buses in each metro area, in "bus_fuels.csv". The fuel types are ULSD, biodiesel, gasoline, ethanol, and CNG.

Overall fuel consumption (gallons/day)	BusFuel.Ma = BusDvmt.Ma / BusMpg.Ma
Fuel consumption by type (gallons/day)	BusFuel.MaFt = BusFuel.Ma * BusFuelProp.MaFt

Truck emissions

MjPerGallon is an input parameter contained in global_values.txt. FuelCo2.Ft is a table showing CO_2e emissions by fuel type, in "fuel_co2.csv".

Energy cons. by fuel type (MJ/day)	TruckMj.MaFt = TruckFuel.MaFt * MjPerGallon
Emissions by fuel type (tonnes/day)	TruckCo2e.MaFt = TruckMj.MaFt *FuelCo2.Ft/1,000,000
Total emissions (tonnes/day)	TruckCo2e.Ma = sum(TruckCo2e.MaFt)

Bus emissions

Energy cons. by fuel type (MJ/day)	BusMj.MaFt = BusFuel.MaFt * MjPerGallon
Emissions by fuel type (tonnes/day)	BusCo2e.MaFt = BusMj.MaFt * FuelCo2.Ft/1,000,000
Total emissions (tonnes/day)	BusCo2e.Ma = sum(BusCo2e.MaFt)

Rail emissions

PowerCo2.Co is a table of county-specific average pounds of CO_2 equivalent emissions per kilowatt hour of electricity consumed by the end user, in "power_co2.csv".

DVMT (miles/day)	RailDvmt.Ma = RailRevMi.Ma * TranAdjFactor / 365
Power consumed (kWh/day)	RailPower.Ma = RailDvmt.Ma / HvyVehMpgMpk.Ag
Average emissions (lbs/kWh)	PowerCo2.Ma = mean(PowerCo2.Co)
Total emissions (tonnes/day)	RailCo2e.Ma = RailPower.Ma * PowerCo2.Ma / 2,204.62262

4 MODEL IMPLEMENTATION PLATFORM

The FHWA tool is implemented in R. R is a freely available language and environment for statistical computing and graphics which provides a wide variety of statistical and graphical techniques: linear and nonlinear modeling, statistical tests, time series analysis, classification, clustering, etc. R is available from the Comprehensive R Archive Network (CRAN),[5] a network of ftp and web servers around the world that store identical up-to-date versions of code and documentation for R. R is an open source version of the S language developed at Bell Laboratories by Chambers et al. R can be used for routine data manipulation and analysis, and the analysis and visualization of model results. Scenario inputs to the FHWA tool 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. The FHWA Tool User's Guide describes how to set up model inputs and run the model.

[5] http://cran.r-project.org/

5 MODEL ESTIMATION DATA

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 (http://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 annual 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.

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

The average amount that each household paid for motor fuel per mile of travel was found to be a highly significant and important variable for predicting household DVMT. However, fuel price and vehicle fuel economy data are not present for all vehicles. Therefore, the vehicle travel model could only be estimated using the households for which data were available. Comparing the model including this variable estimated from the smaller dataset with a model not including this variable estimated from the larger dataset, it was found that the estimates and significance of the other variable coefficients changed little.

Several other sources of data were used to estimate the component models of the FHWA tool, such as U.S. Census public use micro-sample (PUMS) data. They are described in the sections of the report describing the models they were used to estimate.

6 HOUSEHOLD AGE COMPOSITION

County-level forecasts of population by age are primary inputs to the FHWA tool. The forecasts for each county 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 synthesis 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 synthesis process uses a combination of probabilities derived from PUMS data 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 a 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. Moreover, 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 is 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 puts the theoretical limit of the number of household types at 1215. In addition, households in the PUMS data that are composed of persons all under the age of 15 are removed.

Since the PUMS data associate 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. The second control is to create a consistent forecast of the number of households of each type. 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. The method used to resolve the differences in the estimates is the "mean" method that chooses the average of the estimates.
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 per cent or until a maximum number of iterations (default 100).

7 HOUSEHOLD INCOME

A regression model was developed to predict household income from the number and ages of persons in the household and the average per capita income for the region of the state where the household resides. Census PUMS data for Oregon were used for estimating this model and so it does require re-estimation for a new application.

Income data were found to follow a power distribution, so a power transform of income was used as the dependent variable in the model. The chosen exponent (0.4) minimizes the skewness of the income distribution. The model fit was found to be improved if the regional per capita income variable is similarly transformed. The model intercept is set to zero because household income should be zero when the average per capita income is zero or when the household has no persons. Table 1 shows a summary of the model.

The regional per capita income variable and all of the age variables are highly significant. The coefficients for all of the age terms have an appropriate relationship to one another. The contribution of persons to household income rises with age up to the 30 to 54 age group and declines with increasing age.

As might be expected, this regression model does not reproduce the tails of the income distribution, as shown in Figure 2. This could cause several problems if left uncorrected. First, since the income distribution is skewed to the right, the mean predicted value for income will be lower than the mean observed value. Second, since the effects of income on household travel are not linear, improper representation of the tails of the income distribution could cause even greater deficiencies in representing the distribution of household travel and the sensitivity of that travel to changes in costs.

To achieve the proper dispersion of incomes, a procedure for adding random variability was added to the model. The variability in observed income was examined across all model income groups. This variability was found to be fairly uniform. A standard normal distribution is used to add variation to the model predictions of the power transform of income. The addition of this variation results in modeled household incomes nearly matching the observed distribution. This can be seen in Figure 3.

The household income model requires as input the average per capita income (in year 2000 dollars) of the region where the household is located. The model groups counties into regions for this purpose. These regions correspond to Census public use microsample areas (PUMAs), or in the case of several metropolitan areas, groupings of PUMAs.

Table 1: Household Income Model (Oregon specific)

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
PowPerCapInc	0.792567	0.003147	251.818	< 2e-16 ***
Age0to14	-1.00861	0.077073	-13.086	2.99e-10 ***
Age15to19	0.93887	0.149014	6.301	< 2e-16 ***
Age20to29	7.740331	0.119585	64.727	< 2e-16 ***
Age30to54	15.19027	0.111942	135.698	< 2e-16 ***
Age55to64	13.14969	0.148598	88.492	< 2e-16 ***
Age65Plus	8.410674	0.138817	60.588	< 2e-16 ***

Signif. codes: 0 *** 0.001

Residuals

Min	1Q	Median	3Q	Max
-109.4430	-11.1195	0.1774	11.0499	67.8462

Residual standard error: 17.35 on 63502 degrees of freedom
Multiple R-squared: 0.9412, Adjusted R-squared: 0.9412
F-statistic: 1.451e+05 on 7 and 63502 DF, p-value: < 2.2e-16

Figure 2: Observed and Modeled Household Incomes

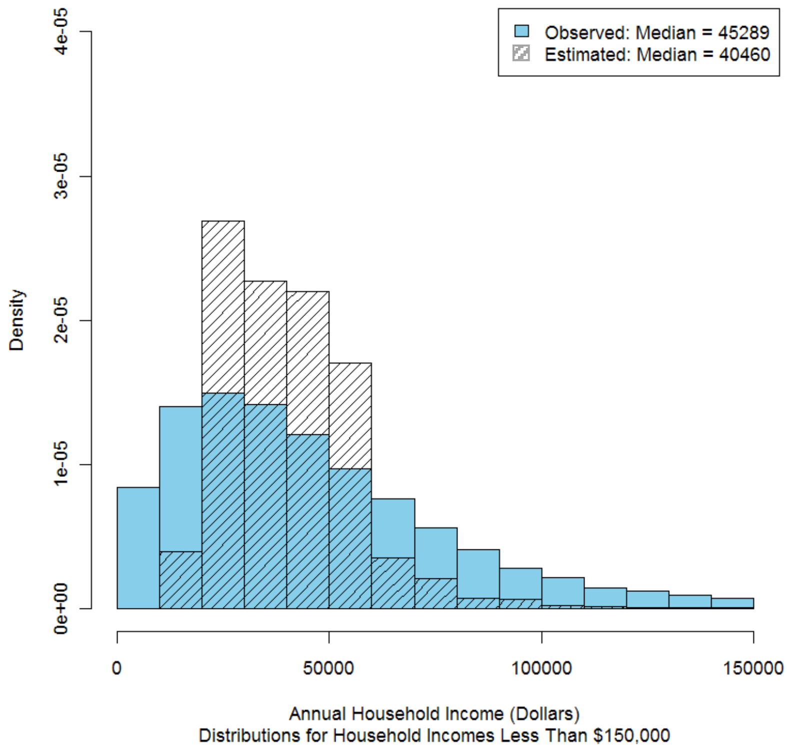
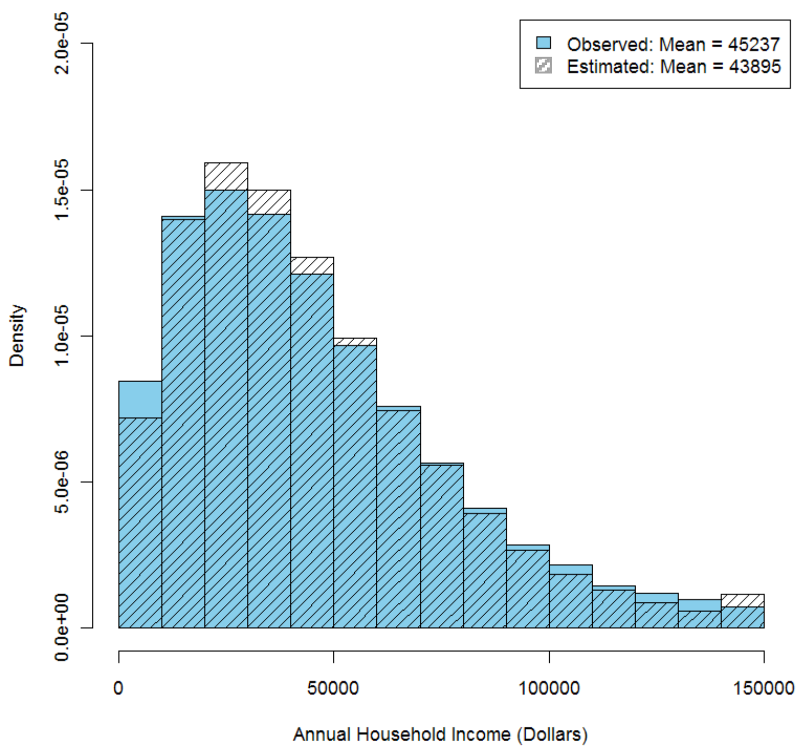


Figure 3: Distribution of Observed and Adjusted Modeled Household Incomes



8 LAND USE CHARACTERISTICS MODELS

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, other urban, 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 the FHWA tool was developed to model GHG mitigation policies at a statewide level. Therefore, models and calculation methods were developed to estimate likely Census tract characteristics for urban areas based on larger-scale characteristics.

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, other urban, or rural.
2. The geographic extent of urban growth in metropolitan and other urban areas in each county is calculated.
3. Overall metropolitan, other urban, and rural densities are calculated.
4. Households are assigned a Census tract population density based on the overall metropolitan, urban, or rural area where they are 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 existing metropolitan amounts/future goals for urban mixed-use development.

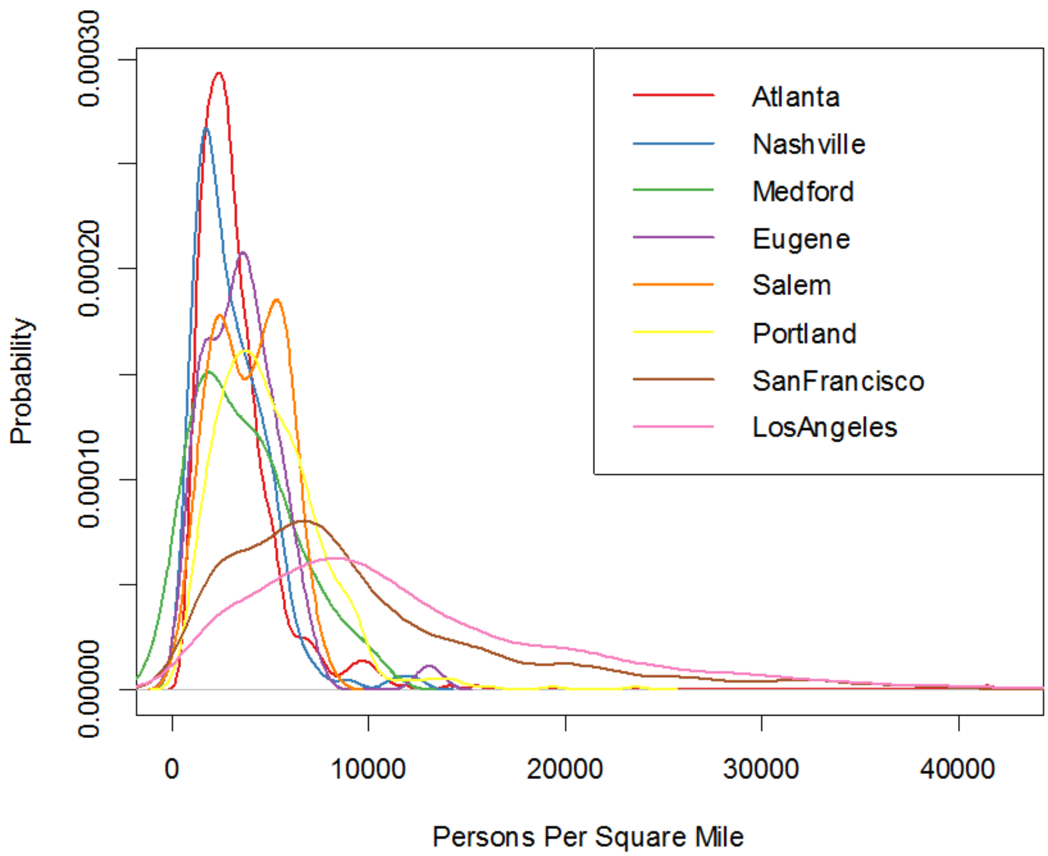
Households in each county are assigned to metropolitan, other urban, and rural development types based on the base year distribution of population by development type and forecasts of the proportions of future population growth by type. The base year distribution is developed from Census data, using Census tract population density as an indicator. Forecasts of proportions of population growth of each type are developed from local sources. 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 and policy inputs which describe how rapidly urban growth boundaries grow relative to population. For example, a value of 0.5 for metropolitan development means that the urban growth area for the metropolitan portion of a county will grow at half the rate of metropolitan population growth.

Overall population densities for metropolitan and other urban areas in each county are computed from the number of households (and hence people) assigned to each development type, and the total urban area computed for each type. For non-metropolitan areas, it is assumed that Census tract densities are approximately equal to overall urban densities since small cities tend to be composed of few Census tracts and population densities in small cities tend to be fairly uniform.

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 4, which compares the Census tract population density distributions of a number of U.S. metropolitan areas.

Figure 4: Population Density Distributions for Selected Metropolitan Areas



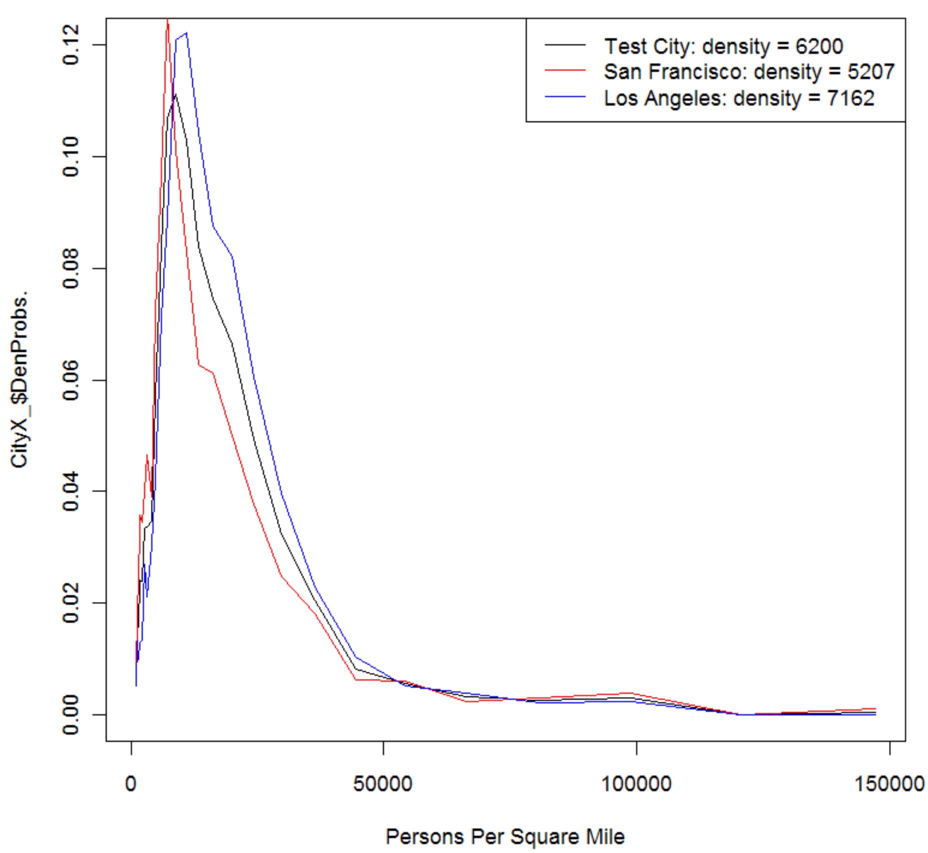
Census tract densities are assigned to metropolitan areas by sampling from distributions such as those shown in Figure 4. Each distribution is associated with a different overall metropolitan density. Higher-density metropolitan areas, like Los Angeles, have density distributions that are broader and the peak is shifted to the right. The model includes several prototype density distributions including Atlanta, Portland, San Francisco, Los Angeles, and several additional prototypes having densities less than Atlanta and greater than Los Angeles. The data on each prototype include the overall average metropolitan density and the distribution of Census tract population densities. The range of densities represented by the prototypes is sufficient to address all land use policies that might be tested. The lower-density prototypes are generated by shifting the Atlanta distribution to the left. The higher-density prototypes are generated by shifting the Los Angeles distribution to the right. The corresponding overall metropolitan area densities for these created prototypes are calculated as the harmonic means of the distributions of population by Census tract density.

The procedure for applying the model to the metropolitan portion of a county is:

1. The overall metropolitan density is calculated from the metropolitan population and the metropolitan area.
2. The overall population density of the metropolitan area is compared to the overall densities of the prototype areas to identify the prototype metropolitan areas that have population densities that bound the subject metropolitan area density.
3. The proportional difference between the overall metropolitan area density and the respective densities of the bounding prototypes is used to compute a weighted average of the population distributions by Census tract density of the two prototypes.
4. The resulting population distribution by Census tract density is used as a sample distribution to assign densities to the households assigned to the metropolitan area.

Figure 5 shows the results of generating a Census tract density distribution for a metropolitan area having an overall density between those of San Francisco and Los Angeles. The model process produces a Census tract density distribution that is between the prototype density distributions.

Figure 5: Test Generation of Metropolitan Census Tract Density Distribution



For rural areas, a uniform population density is assumed for the rural portions of each county. 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. For forecast years, it is assumed that additional rural population will be added at a density of one household per two acres. The new development is averaged with the base year density to arrive at the forecast rural density.

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 FHWA tool 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.[6] 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.[7]

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

[6] 2001 National Household Travel Survey. *User's Guide,* p. Q3.

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

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 2 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 3 shows that the residual deviance of a binary logit model to predict urban mixed-use type based on population density is relatively high.

Table 2: Comparison of Population Density and "Urban" Type of Households

Population Density	% of Households that are Urban Type	Distribution of Urban Type Households (%)	Total Number of Households
50	0	0	9,653
300	0.1	0.2	10,079
750	0.3	0.3	4,971
1500	0.8	1.0	6,639
3000	3.9	6.6	9,754
7000	19.9	32.5	9,399
17000	67.8	33.0	2,809
30000	95.5	26.4	1,592

Although the "urban"classification is not determined solely by the population density of the Census tract, 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 3 shows a summary of the model.

Table 3: Urban Mixed-Use Development Type Model

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-3.16E+00	3.93E-02	-80.44	< 2e-16 ***
Htppopdn	2.80E-04	4.48E-06	62.5	< 2e-16 ***

Signif. codes: 0 *** 0.001

Deviance Residuals

Min	1Q	Median	3Q	Max
-3.2416	-0.4326	-0.3533	0.1024	2.5263

(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

The amount of urban mixed-use development, however, is not just a deterministic property of a metropolitan area. It is also affected by land use policies, and the model needs to reflect the effects of policies aimed at changing the amount of this development. To accommodate testing of the effects of more or less urban mixed-use development, the user can input a target urban mixed-use proportion for each metropolitan area and the intercept for the model shown in Table 3 will be iteratively adjusted until the overall urban proportion is within 0.01 of the input proportion. Not all possible targets are achievable, however, given the form of the model equation. For example, it is unrealistic to expect a high percentage of urban mixed-use development in a metropolitan area having a low overall population density. The function that implements the iterative adjustment will stop when further adjustment to the mixed-use proportion is infeasible.

9 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 straightforward. The model data include year 2000 inventories of freeway lane-miles, arterial lane-miles, and transit revenue-miles by metropolitan area. Future year growth rates of freeway and arterial lane-miles are specified relative to metropolitan area population growth rates. For example, a value of one for freeway supply growth means that freeway lane-miles grow in direct proportion to population growth. If metropolitan area population doubles, then freeway lane-miles will double as well and per capita freeway lane-miles will remain unchanged. Since the amount of population growth for each metropolitan area is computed in the previous step, it is a simple matter to compute future freeway and arterial supplies given the growth rate assumptions. Growth of future transit supplies is specified relative to base year per capita transit supplies. A value of 2 means that transit revenue miles per capita doubles.

The user must also input the assumed portion of public transit supply growth that will be electric rail (e.g. light rail or trolley). This is used to compute the amounts of fuels vs. electric power to provide future public transit service.

10 VEHICLE OWNERSHIP MODEL

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 4 to 14 show the statistics for models for metropolitan households with zero vehicles, less than one vehicle, one vehicle, and greater than one vehicle, 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

Table 4: Metropolitan Area Zero-Vehicle Household Models - One Driving Age Person in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-6.83E-01	2.44E-01	-2.8	0.005108	**
Hhincttl	-1.10E-04	8.84E-06	-12.484	< 2e-16	***
Htppopdn	1.10E-04	4.00E-05	2.739	0.006159	**
Tranmilescap	-3.62E-02	1.11E-02	-3.273	0.001063	**
Urban	1.03E+00	2.17E-01	4.731	2.23E-06	***
Hhincttl:Htppopdn	9.06E-10	3.25E-10	2.791	0.005259	**
Hhincttl:Tranmilescap	9.50E-07	2.45E-07	3.886	0.000102	***
Hhincttl:Urban	1.97E-05	7.41E-06	2.662	0.007772	**
Htppopdn:Tranmilescap	9.63E-07	4.49E-07	2.144	0.032065	*
Htppopdn:Urban	-5.51E-05	1.53E-05	-3.602	0.000316	***
Htppopdn:Fwylnmicap	-1.19E-04	5.15E-05	-2.315	0.020601	*
Tranmilescap:Fwylnmicap	5.77E-02	2.06E-02	2.803	0.005059	**

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05

Table 5: Metropolitan Area Zero-Vehicle Household Models - Two Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.43E+00	1.48E-01	-9.634	< 2e-16	***
Hhincttl	-6.79E-05	5.00E-06	-13.589	< 2e-16	***
Hhincttl:Htppopdn	1.42E-09	1.98E-10	7.152	8.53E-13	***
Hhincttl:OnlyElderly	-3.55E-05	7.05E-06	-5.041	4.64E-07	***
Htppopdn:Tranmilescap	1.85E-06	1.66E-07	11.124	< 2e-16	***

Signif. codes: 0 *** 0.001

Table 6: Metropolitan Area Zero-Vehicle Household Models - Three or More Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-3.49E+00	4.86E-01	-7.188	6.57E-13	***
Hhincttl	-4.90E-05	8.12E-06	-6.04	1.54E-09	***
Htppopdn	9.72E-05	1.76E-05	5.513	3.53E-08	***
Hhincttl:Htppopdn	7.31E-10	3.58E-10	2.04	4.14E-02	*
Tranmilescap:Fwylnmicap	7.55E-02	2.28E-02	3.308	0.000938	***

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05

Table 7: Metropolitan Area <1-Vehicle per Driving Age Person Household Models - Two Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-2.63E-01	9.58E-02	-2.743	0.006095	**
Hhincttl	-4.59E-05	2.31E-06	-19.893	< 2e-16	***
Htppopdn	5.65E-05	1.33E-05	4.235	2.28E-05	***
OnlyElderly	1.74E+00	3.27E-01	5.302	1.15E-07	***
Hhincttl:Htppopdn	1.19E-09	9.59E-11	12.434	< 2e-16	***
Hhincttl:Tranmilescap	3.34E-07	5.09E-08	6.566	5.15E-11	***
Hhincttl:OnlyElderly	9.36E-06	2.66E-06	3.516	0.000438	***
Htppopdn:Tranmilescap	-1.43E-06	2.44E-07	-5.843	5.13E-09	***
Htppopdn:Urban	-4.75E-05	1.01E-05	-4.694	2.68E-06	***
Htppopdn:OnlyElderly	-2.71E-05	9.64E-06	-2.811	0.004933	**
Tranmilescap:Urban	2.95E-02	3.84E-03	7.677	1.63E-14	***
OnlyElderly:Tranmilescap	-1.29E-02	5.22E-03	-2.47	0.013501	*

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05

Table 8: Metropolitan Area <1-Vehicle per Driving Age Person Household Models - Three or More Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	9.34E-01	1.03E-01	9.089	< 2e-16	***
Hhincttl	-1.83E-05	1.52E-06	-12.042	< 2e-16	***
OnlyElderly	5.21E+00	2.32E+00	2.24	0.0251	*
Hhincttl:Tranmilescap	1.66E-07	3.03E-08	5.475	4.38E-08	***
Hhincttl:Urban	1.31E-05	2.09E-06	6.283	3.32E-10	***
Hhincttl:OnlyElderly	-1.20E-04	5.43E-05	-2.216	0.0267	*
Urban:Htppopdn	-4.89E-05	9.92E-06	-4.935	8.01E-07	***
Htppopdn:Fwylnmicap	8.93E-05	1.91E-05	4.686	2.79E-06	***
Urban:Fwylnmicap	-6.89E-01	3.26E-01	-2.112	0.0347	*

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05

Table 9: Metropolitan Area One-Vehicle per Driving Age Person Household Models - One Driving Age Person in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	6.22E-01	1.05E-01	5.951	2.67E-09	***
Tranmilescap	2.33E-02	4.73E-03	4.92	8.65E-07	***
Hhincttl:Htppopdn	1.13E-09	1.25E-10	9.09	< 2e-16	***
Tranmilescap:Hhincttl	-2.76E-07	5.17E-08	-5.342	9.17E-08	***
Hhincttl:OnlyElderly	7.20E-06	2.71E-06	2.654	0.00796	**
Tranmilescap:Htppopdn	-1.66E-06	2.24E-07	-7.436	1.04E-13	***
Htppopdn:Urban	-4.54E-05	7.85E-06	-5.779	7.50E-09	***
Htppopdn:Fwylnmicap	4.08E-05	1.64E-05	2.484	0.01298	*
Tranmilescap:OnlyElderly	-7.76E-03	3.34E-03	-2.326	0.02004	*

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05

Table 10: Metropolitan Area One-Vehicle per Driving Age Person Household Models - Two Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	1.53E-01	6.95E-02	2.204	0.027558	*
Hhincttl	5.79E-06	8.57E-07	6.755	1.43E-11	***
Htppopdn	4.02E-05	1.16E-05	3.479	0.000503	***
Urban	-3.81E-01	1.62E-01	-2.349	0.018817	*
OnlyElderly	-5.54E-01	1.21E-01	-4.575	4.77E-06	***
Hhincttl:Htppopdn	2.41E-10	1.20E-10	2.008	0.044633	*
Hhincttl:Urban	8.18E-06	2.12E-06	3.864	0.000112	***
Hhincttl:OnlyElderly	7.11E-06	2.14E-06	3.322	0.000894	***
Htppopdn:Tranmilescap	-1.79E-06	2.10E-07	-8.519	< 2e-16	***
Htppopdn:Urban	-4.94E-05	8.97E-06	-5.509	3.61E-08	***

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05

Table 11: Metropolitan Area One-Vehicle per Driving Age Person Household Models - Three or More Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.28E+00	1.27E-01	-10.099	< 2e-16	***
Hhincttl	7.91E-06	1.42E-06	5.555	2.78E-08	***
Htppopdn	-5.76E-05	1.66E-05	-3.472	0.000517	***
Hhincttl:Htppopdn	5.38E-10	1.81E-10	2.975	0.002928	**
Tranmilescap:Urban	-2.04E-02	4.39E-03	-4.64	3.49E-06	***

Signif. codes: 0 *** 0.001 ** 0.01

Table 12: Metropolitan Area >1-Vehicle per Driving Age Person Household Models - One Driving Age Person in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.75E+00	1.02E-01	-17.089	< 2e-16	***
Hhincttl	1.61E-05	1.32E-06	12.195	< 2e-16	***
Htppopdn	-5.67E-05	1.92E-05	-2.953	0.003152	**
OnlyElderly	-1.02E+00	2.70E-01	-3.782	0.000156	***
Htppopdn:Tranmilescap	-1.19E-06	4.23E-07	-2.801	0.005097	**
Htppopdn:Urban	4.53E-05	1.74E-05	2.61	0.009065	**
Urban:Fwylnmicap	-9.46E-01	2.83E-01	-3.336	0.000848	***
OnlyElderly:Fwylnmicap	1.11E+00	4.19E-01	2.643	0.008227	**

Signif. codes: 0 *** 0.001 ** 0.01

Table 13: Metropolitan Area >1-Vehicle per Driving Age Person Household Models - Two Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.96E+00	1.21E-01	-16.164	< 2e-16	***
Hhincttl	7.57E-06	9.77E-07	7.75	9.19E-15	***
Fwylnmicap	7.64E-01	1.54E-01	4.944	7.65E-07	***
OnlyElderly	-6.65E-01	9.62E-02	-6.912	4.77E-12	***
Hhincttl:Htppopdn	5.78E-10	1.55E-10	3.725	0.000195	***
Htppopdn:Tranmilescap	-1.27E-06	3.29E-07	-3.841	0.000123	***
Htppopdn:Urban	2.87E-05	1.42E-05	2.012	0.04425	*
Fwylnmicap:Htppopdn	-1.56E-04	2.39E-05	-6.52	7.03E-11	***
Tranmilescap:Urban	-2.27E-02	5.74E-03	-3.961	7.47E-05	***

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05

Table 14: Metropolitan Area >1-Vehicle per Driving Age Person Household Models - Three or More Driving Age Persons in Household

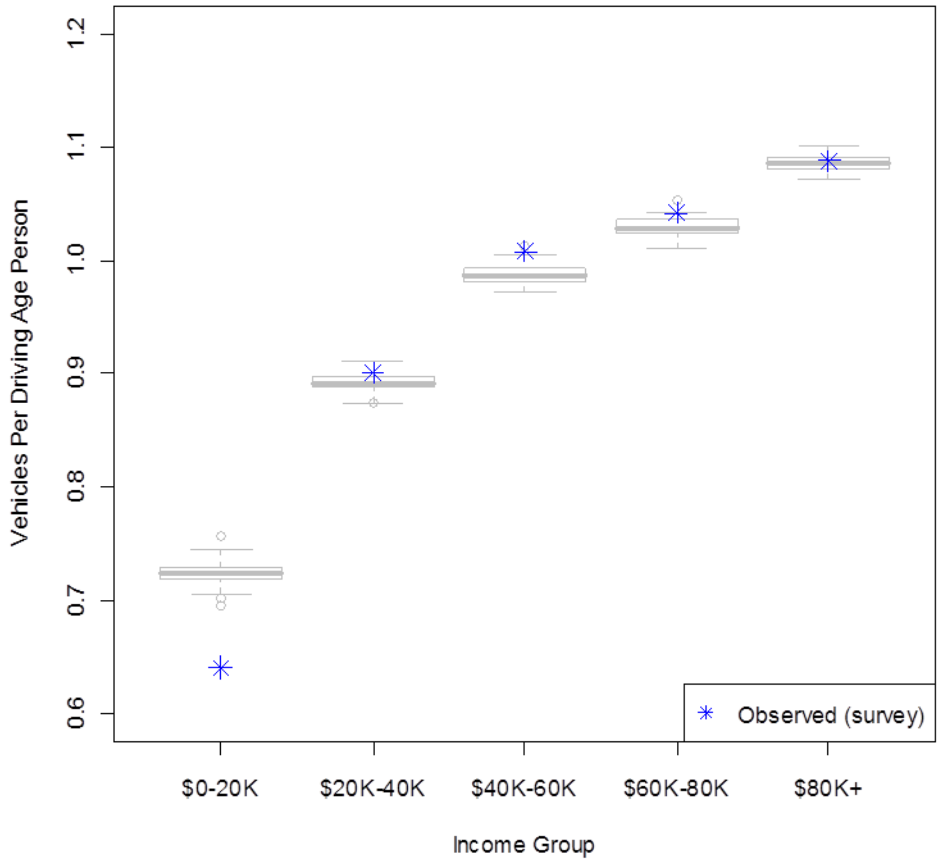
	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.00E+00	1.14E-01	-8.751	< 2e-16	***
Htppopdn	-3.01E-04	3.55E-05	-8.478	< 2e-16	***
Tranmilescap	-1.29E-02	3.71E-03	-3.462	0.000537	***
Htppopdn:Hhincttl	2.21E-09	3.31E-10	6.659	2.76E-11	***

Signif. codes: 0 *** 0.001

The estimated percentages of households by vehicle ownership category for each household income group 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 6 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. 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 6: Observed and Estimated Mean Vehicle Ownership Ratios for Metropolitan Households by Income Group



Tables 15 to 23 show the statistics for the non-metropolitan area models for households with zero vehicles, less than one vehicle, one vehicle, and greater than one vehicle, 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 15: Non-Metro Area Zero-Vehicle Household Models - One Driving Age Person in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-7.65E-01	9.16E-02	-8.35	< 2e-16	***
Hhincttl	-9.49E-05	5.07E-06	-18.712	< 2e-16	***
Htppopdn	5.59E-05	1.26E-05	4.424	9.67E-06	***
Hhincttl:Htppopdn	1.55E-09	4.42E-10	3.509	0.00045	***
Htppopdn:OnlyElderly	3.45E-05	1.26E-05	2.746	0.00604	**

Signif. codes: 0 *** 0.001 ** 0.01

Table 16: Non-Metro Area Zero-Vehicle Household Models - Two Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.97E+00	1.58E-01	-12.51	< 2e-16	***
Hhincttl	-8.50E-05	5.67E-06	-14.982	< 2e-16	***
Htppopdn	9.49E-05	1.24E-05	7.663	1.82E-14	***
OnlyElderly	-7.51E-01	2.32E-01	-3.237	0.00121	**
Htppopdn:OnlyElderly	6.91E-05	3.02E-05	2.287	0.02222	*

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05

Table 17: Non-Metro Area Zero-Vehicle Household Models - Three or More Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-3.18E+00	3.13E-01	-10.155	< 2e-16	***
Hhincttl	-5.00E-05	8.05E-06	-6.21	5.29E-10	***
Htppopdn	1.33E-04	2.14E-05	6.229	4.68E-10	***

Signif. codes: 0 *** 0.001

Table 18: Non-Metro Area <1-Vehicle Per Driving Age Person Household Models - Two Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-4.14E-01	6.27E-02	-6.596	4.22E-11	***
Hhincttl	-3.93E-05	1.43E-06	-27.452	< 2e-16	***
Htppopdn	4.71E-05	1.04E-05	4.548	5.43E-06	***
OnlyElderly	3.04E-01	9.55E-02	3.179	0.00148	**
Hhincttl:Htppopdn	9.68E-10	2.00E-10	4.832	1.35E-06	***
Hhincttl:OnlyElderly	1.54E-05	2.32E-06	6.624	3.51E-11	***

Signif. codes: 0 *** 0.001 ** 0.01

Table 19: Non-Metro Area <1-Vehicle Per Driving Age Person Household Models - Three or More Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	4.82E-01	5.98E-02	8.049	8.36E-16	***
Hhincttl	-1.26E-05	8.47E-07	-14.898	< 2e-16	***
Htppopdn	9.05E-05	9.44E-06	9.588	< 2e-16	***
OnlyElderly	1.83E+00	4.89E-01	3.745	0.000181	***

Signif. codes: 0 *** 0.001

Table 20: Non-Metro Area One-Vehicle Per Driving Age Person Household Models - One Driving Age Person in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	9.73E-01	6.13E-02	15.887	< 2e-16	***
Hhincttl	-9.72E-06	1.44E-06	-6.768	1.30E-11	***
Htppopdn	-2.84E-05	1.11E-05	-2.559	0.0105	*
OnlyElderly	2.55E-01	9.35E-02	2.723	0.00647	**
Hhincttl:Htppopdn	1.49E-09	2.92E-10	5.123	3.01E-07	***
Hhincttl:OnlyElderly	6.46E-06	2.57E-06	2.519	0.01177	*
Htppopdn:OnlyElderly	-2.76E-05	1.30E-05	-2.115	0.03443	*

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05

Table 21: Non-Metro Area One-Vehicle Per Driving Age Person Household Models - Two Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	2.44E-01	4.02E-02	6.082	1.19E-09	***
Hhincttl	2.21E-06	6.31E-07	3.508	0.000451	***
Htppopdn	-5.87E-05	1.01E-05	-5.821	5.85E-09	***
OnlyElderly	-3.62E-01	7.92E-02	-4.575	4.76E-06	***
Hhincttl:Htppopdn	1.29E-09	1.79E-10	7.184	6.77E-13	***
Hhincttl:OnlyElderly	7.84E-06	1.57E-06	4.98	6.36E-07	***
Htppopdn:OnlyElderly	-5.58E-05	1.45E-05	-3.854	0.000116	***

Signif. codes: 0 *** 0.001

Table 22: Non-Metro Area One-Vehicle Per Driving Age Person Household Models - Three or More Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.09E+00	6.34E-02	-17.167	< 2e-16	***
Hhincttl	7.32E-06	8.47E-07	8.632	< 2e-16	***
Htppopdn	-5.23E-05	1.00E-05	-5.225	1.74E-07	***

Signif. codes: 0 *** 0.001

Table 23: Non-Metro Area >1-Vehicle Per Driving Age Person Household Models - One Driving Age Person in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.51E+00	5.87E-02	-25.739	< 2e-16	***
Hhincttl	1.98E-05	1.17E-06	16.867	< 2e-16	***
Htppopdn	-1.01E-04	1.11E-05	-9.137	< 2e-16	***
OnlyElderly	-5.03E-01	8.01E-02	-6.273	3.54E-10	***
Htppopdn:OnlyElderly	-8.93E-05	2.96E-05	-3.019	0.00254	**

Signif. codes: 0 *** 0.001 **

Table 24: Non-Metro Area >1-Vehicle Per Driving Age Person Household Models - Two Driving Age Persons in Household

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.29E+00	4.01E-02	-32.201	<2e-16	***
Hhincttl	9.13E-06	5.56E-07	16.409	<2e-16	***
Htppopdn	-1.28E-04	8.58E-06	-14.862	<2e-16	***
OnlyElderly	-5.89E-01	6.58E-02	-8.946	<2e-16	***
Htppopdn:OnlyElderly	-6.49E-05	3.09E-05	-2.101	0.0357	*

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05

Table 25: Non-Metro Area >1-Vehicle Per Driving Age Person Household Models - Three or More Driving Age Persons in Household

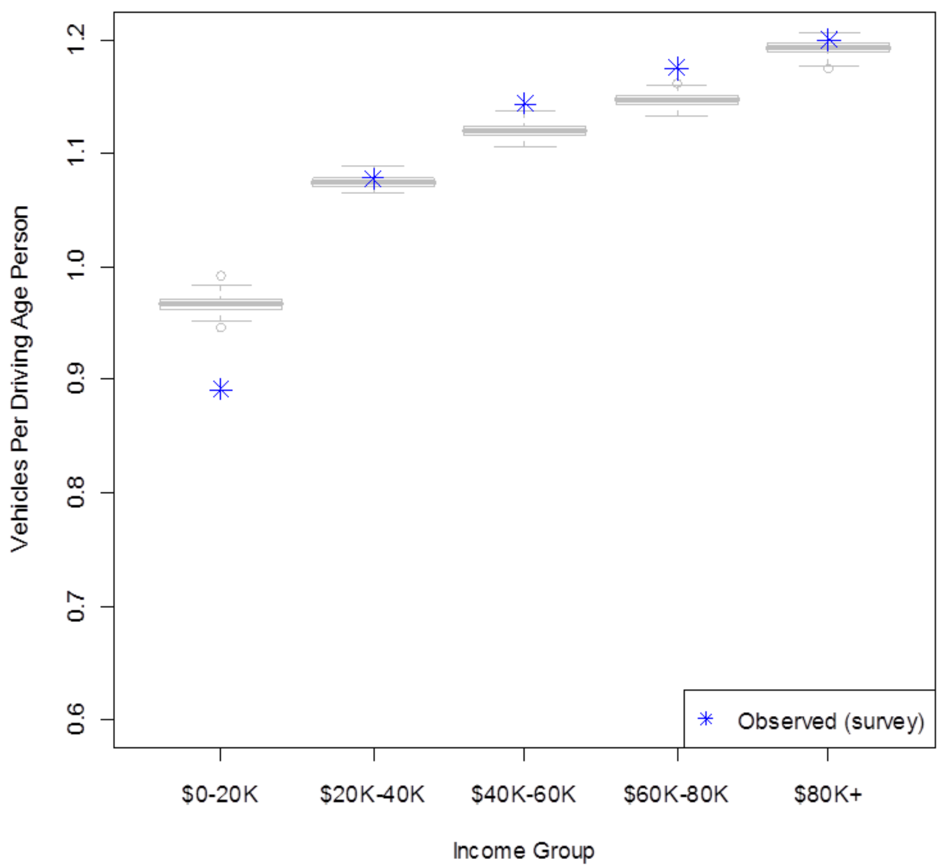
	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.89E+00	7.76E-02	-24.413	<2e-16	***
Hhincttl	1.03E-05	9.97E-07	10.364	<2e-16	***
Htppopdn	-1.28E-04	1.58E-05	-8.089	6.01E-16	***

Signif. codes: 0 *** 0.001

The estimated percentages of households by vehicle ownership category for each household income group 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 exist 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 7 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 7: 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.

11 HOUSEHOLD VEHICLE TRAVEL MODEL

The household vehicle travel model component is the most important component of the FHWA tool. 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 (such as freeway lanes-miles), 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.

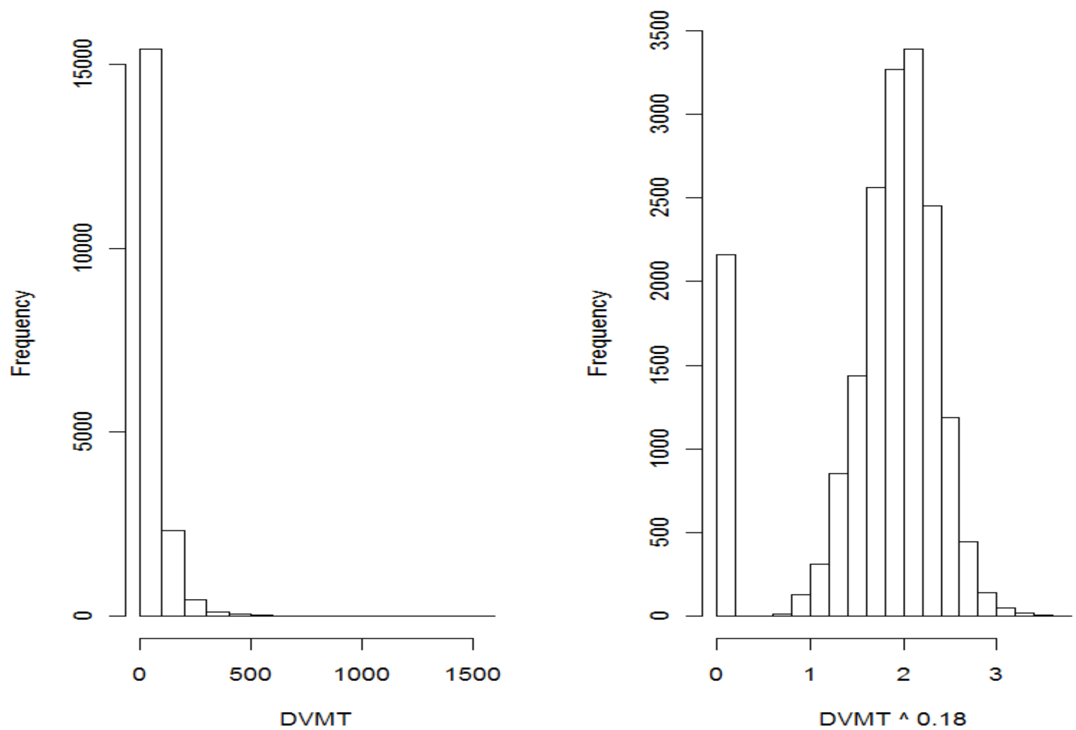
This model component is also the most complex to estimate because data on the average household DVMT are not included in the survey and must be imputed. This is done using simulation. Metropolitan and non-metropolitan models are estimated to determine the probability that a household engages in no vehicle 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 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 estimate the distribution of likely household DVMT on any given day. The stochastic household travel model has two components. The first component is implemented with a binomial logit model that determines the likelihood that a household engages in no vehicle travel for the day. 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 8. 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 8: 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 with the other DVMT households would distort the model.

The zero DVMT household model is a binary logit model that predicts the probability that a household does no vehicle travel. As with other household models in the FHWA tool, 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 26 shows the metropolitan model coefficients and statistics. Table 27 shows this information for the non-metropolitan 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 26: Metropolitan Area Zero DVMT Household Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	3.70E+00	3.44E-01	10.767	<2e-16	***
DrvAgePop	-5.22E-01	4.49E-02	-11.635	<2e-16	***
LogIncome	-4.86E-01	3.47E-02	-14.023	<2e-16	***
Htppopdn	2.98E-05	4.54E-06	6.569	5.08E-11	***
Age65Plus	3.20E-01	3.88E-02	8.232	<2e-16	***
Tranmilescap	8.37E-03	2.18E-03	3.836	0.000125	***
Hhvehcnt	-3.61E-01	4.76E-02	-7.582	3.39E-14	***
ZeroVeh	3.43E+00	1.23E-01	27.905	<2e-16	***
Tranmilescap:Urban	1.09E-02	2.37E-03	4.578	4.68E-06	***

Signif. codes: 0 *** 0.001 (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 27: Non-Metropolitan Area Zero DVMT Household Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	4.86E+00	2.56E-01	18.967	<2e-16	***
DrvAgePop	-6.30E-01	4.13E-02	-15.266	<2e-16	***
LogIncome	-5.77E-01	2.66E-02	-21.685	<2e-16	***
Htppopdn	2.11E-05	4.95E-06	4.264	2.00E-05	***
Hhvehcnt	-1.75E-01	2.91E-02	-6.017	1.78E-09	***
ZeroVeh	3.44E+00	1.08E-01	31.938	<2e-16	***
Age30to54	-1.08E-01	3.73E-02	-2.895	0.00379	**
Age65Plus	3.77E-01	3.38E-02	11.142	<2e-16	***

Signif. codes: 0 *** 0.001 ** 0.01 (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 characteristics, 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 28 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.

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 29 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 28: Metropolitan Area Household DVMT Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	7.81E-01	4.64E-02	16.836	<2e-16	***
Age65Plus	-7.18E-02	4.22E-03	-17.033	<2e-16	***
LogIncome	8.69E-02	4.24E-03	20.498	<2e-16	***
Htppopdn	-3.69E-06	1.14E-06	-3.236	0.00121	**
Fwylnmicap	3.38E-02	1.61E-02	2.107	0.03511	*
Urban	-5.18E-02	8.64E-03	-5.989	2.16E-09	***
Hhvehcnt	6.09E-02	3.23E-03	18.821	<2e-16	***
DrvAgePop	7.23E-02	3.68E-03	19.652	<2e-16	***
Htppopdn:Tranmilescap	-5.98E-08	2.65E-08	-2.259	0.02391	*

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05
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

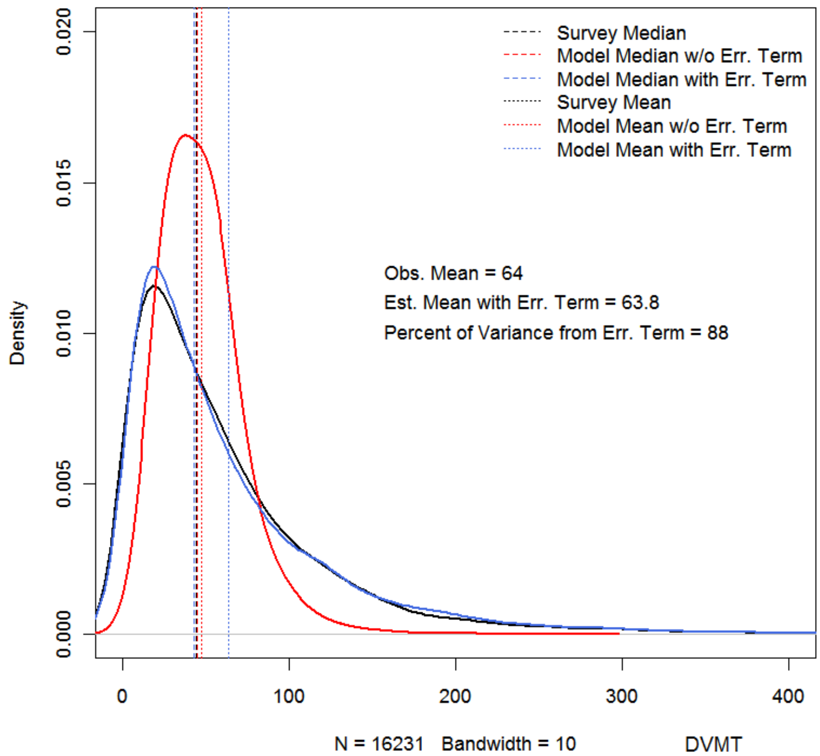
Table 29: Non-Metropolitan Area Household DVMT Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	9.23E-01	2.47E-02	37.439	<2e-16	***
Census_rMidwest	-1.24E-02	4.05E-03	-3.057	0.002239	**
Census_rSouth	3.03E-02	4.77E-03	6.359	2.06E-10	***
Census_rWest	-2.65E-02	5.60E-03	-4.731	2.25E-06	***
LogIncome	5.80E-02	2.41E-03	24.111	<2e-16	***
Hhvehcnt	3.42E-02	1.62E-03	21.134	<2e-16	***
ZeroVeh	-4.92E-02	2.32E-02	-2.118	0.034149	*
Htppopdn	-5.50E-06	1.21E-06	-4.544	5.53E-06	***
Age0to14	8.72E-03	1.82E-03	4.79	1.68E-06	***
Age15to19	3.67E-02	3.36E-03	10.918	<2e-16	***
Age20to29	9.39E-02	4.04E-03	23.215	<2e-16	***
Age30to54	8.37E-02	3.72E-03	22.499	<2e-16	***
Age55to64	7.60E-02	4.14E-03	18.37	<2e-16	***
Age65Plus	3.23E-02	3.92E-03	8.242	<2e-16	***
Htppopdn:Age20to29	-1.82E-06	8.33E-07	-2.185	0.028904	*
Htppopdn:Age30to54	-3.36E-06	7.08E-07	-4.749	2.05E-06	***
Htppopdn:Age55to64	-3.42E-06	9.55E-07	-3.584	0.000338	***
Htppopdn:Age65Plus	-2.76E-06	8.83E-07	-3.13	0.001747	**

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05
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. 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 9). 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 9 shows that when untransformed, the model distribution with the added error term (blue line) matches the survey distribution (black line) very well, and the mean values are nearly the same.

Figure 9: Observed and Estimated Distributions of DVMT for Metropolitan Households

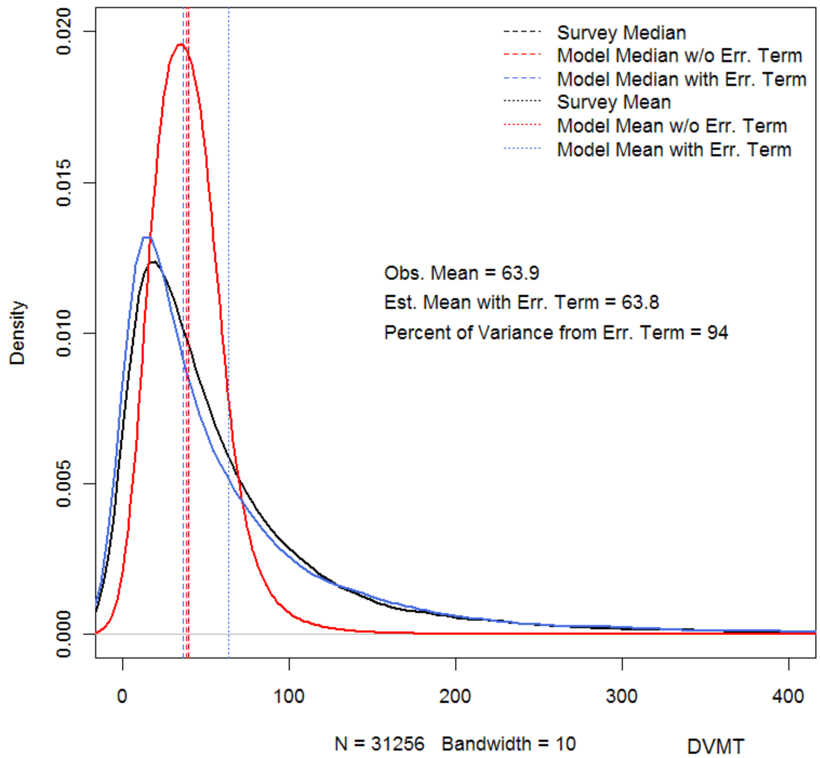


The same process was used to match the non-metropolitan model distribution to the survey distribution. Figure 10 shows the observed and estimated DVMT distributions for non-metropolitan households.

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, 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 10: 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.[8] 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.

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

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

reduce the amount of stochastic variation occurring in the FHWA tool 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 for 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 30 shows the results for the metropolitan area model and Table 31 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. 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 32 to 35 show the estimation results for metropolitan area and non-metropolitan area households. 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,

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 11 and 12 respectively.

Table 30: Metropolitan Area Household Average DVMT Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	6.47E-01	2.88E-03	224.404	<2e-16	***
Census_rMidwest	7.17E-05	5.91E-04	0.121	0.90352	
Census_rSouth	-7.35E-04	4.81E-04	-1.526	0.12695	
Census_rWest	1.55E-03	5.90E-04	2.621	0.00876	**
LogIncome	1.07E-01	2.52E-04	426.739	<2e-16	***
Htppopdn	-3.16E-06	7.52E-08	-42.015	<2e-16	***
Hhvehcnt	5.80E-02	2.20E-04	263.031	<2e-16	***
ZeroVeh	-5.90E-01	7.51E-04	-785.642	<2e-16	***
Tranmilescap	-1.76E-04	2.04E-05	-8.619	<2e-16	***
Fwylnmicap	3.37E-02	1.21E-03	27.861	<2e-16	***
DrvAgePop	8.57E-02	2.42E-04	354.698	<2e-16	***
Age65Plus	-7.68E-02	2.72E-04	-281.995	<2e-16	***
Urban	-6.13E-02	5.50E-04	-111.38	<2e-16	***
Htppopdn:Tranmilescap	-1.15E-07	1.72E-09	-67.18	<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 31: Non-Metropolitan Area Household Average DVMT Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	8.22E-01	1.46E-03	562.07	<2e-16	***
Census_rMidwest	-3.62E-04	2.52E-04	-1.438	0.1503	
Census_rSouth	6.06E-04	2.97E-04	2.04	0.0413	*
Census_rWest	1.29E-04	3.48E-04	0.37	0.7112	
LogIncome	7.38E-02	1.44E-04	513.161	<2e-16	***
Hhvehcnt	3.25E-02	1.04E-04	312.23	<2e-16	***
ZeroVeh	-4.70E-01	5.36E-04	-877.139	<2e-16	***
DrvAgePop	1.17E-02	6.28E-04	18.57	<2e-16	***
Htppopdn	-5.80E-06	6.98E-08	-83.037	<2e-16	***
Age0to14	8.96E-03	1.17E-04	76.605	<2e-16	***
Age15to19	2.91E-02	6.62E-04	43.997	<2e-16	***
Age20to29	8.95E-02	6.70E-04	133.608	<2e-16	***
Age30to54	8.14E-02	6.57E-04	123.852	<2e-16	***
Age55to64	7.40E-02	6.63E-04	111.64	<2e-16	***
Age65Plus	2.39E-02	6.58E-04	36.243	<2e-16	***
Htppopdn:Age20to29	-1.43E-06	4.93E-08	-28.981	<2e-16	***
Htppopdn:Age30to54	-2.81E-06	4.22E-08	-66.624	<2e-16	***
Htppopdn:Age55to64	-3.07E-06	5.79E-08	-53.147	<2e-16	***
Htppopdn:Age65Plus	-2.66E-06	5.28E-08	-50.413	<2e-16	***

Signif. codes: 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

Table 32: Metropolitan Area Household 95th Percentile Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	7.82E+00	1.02E-01	76.81	<2e-16	***
DvmtAve	3.06E+00	4.63E-03	662.22	<2e-16	***
DvmtAveSq	-7.59E-03	5.98E-05	-127.02	<2e-16	***
DvmtAveCu	1.83E-05	2.06E-07	88.94	<2e-16	***

Signif. codes: 0 *** 0.001
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

Table 33: Metropolitan Area Household Maximum DVMT Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	5.00E+01	3.75E-01	133.48	<2e-16	***
DvmtAve	5.28E+00	1.70E-02	309.89	<2e-16	***
DvmtAveSq	-1.39E-02	2.20E-04	-63.2	<2e-16	***
DvmtAveCu	3.07E-05	7.58E-07	40.48	<2e-16	***

Signif. codes: 0 *** 0.001
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 34: Non-Metropolitan Area Household 95th Percentile Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	1.59E+01	9.31E-02	170.46	<2e-16	***
DvmtAve	3.07E+00	2.70E-03	1137.5	<2e-16	***
DvmtAveSq	-2.34E-03	1.97E-05	-118.6	<2e-16	***
DvmtAveCu	1.62E-06	1.97E-08	82.35	<2e-16	***

Signif. codes: 0 *** 0.001
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

Table 35: Non-Metropolitan Area Household Maximum DVMT Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	8.08E+01	4.56E-01	177.35	<2e-16	***
DvmtAve	6.28E+00	1.32E-02	475.9	<2e-16	***
DvmtAveSq	-6.88E-03	9.66E-05	-71.24	<2e-16	***
DvmtAveCu	4.66E-06	9.62E-08	48.46	<2e-16	***

Signif. codes: 0 *** 0.001
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

Figure 11: Comparison of Simulated and Estimated Distributions of Average DVMT, 95th Percentile DVMT, and Maximum DVMT for Metropolitan Area Households

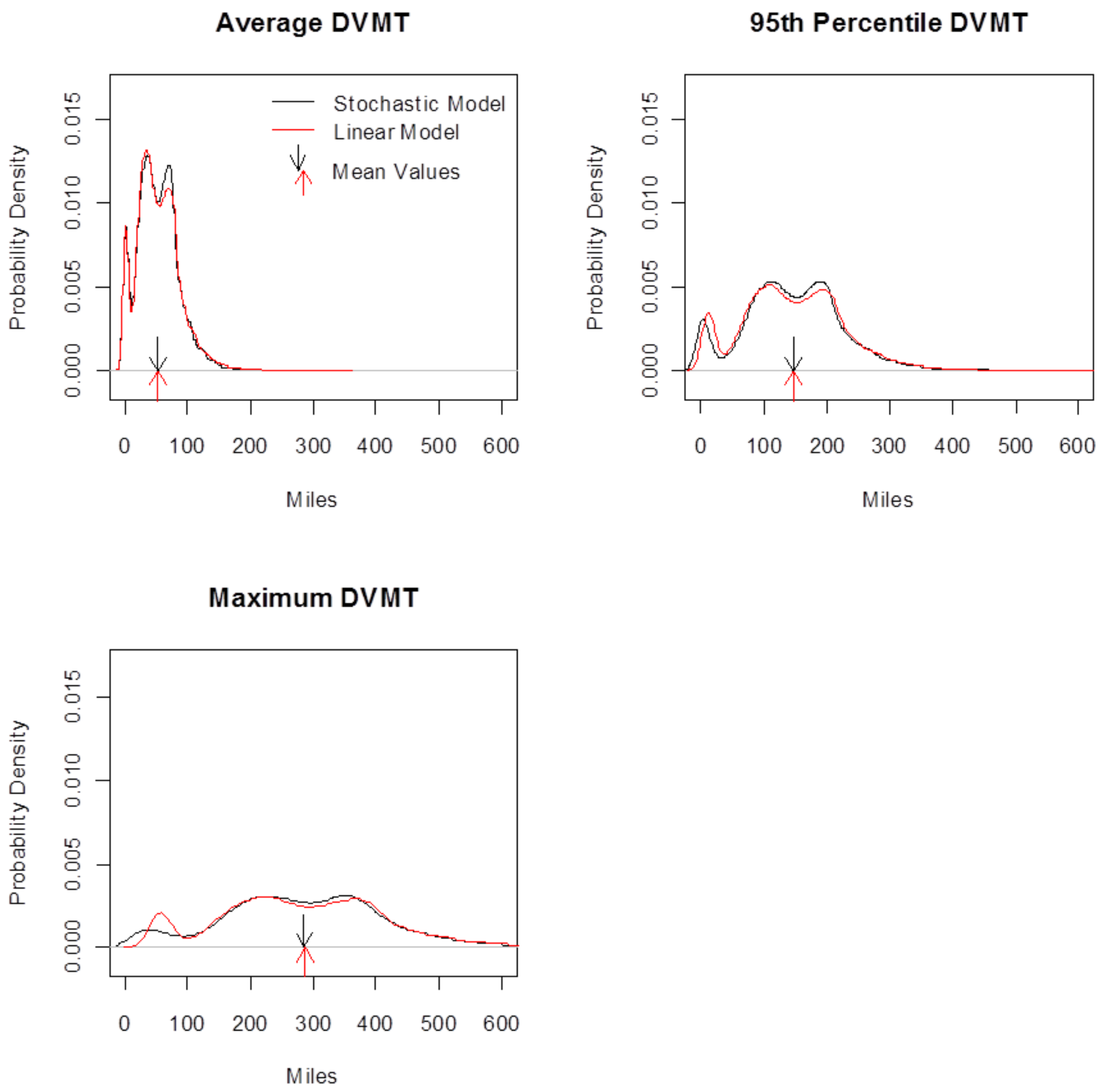
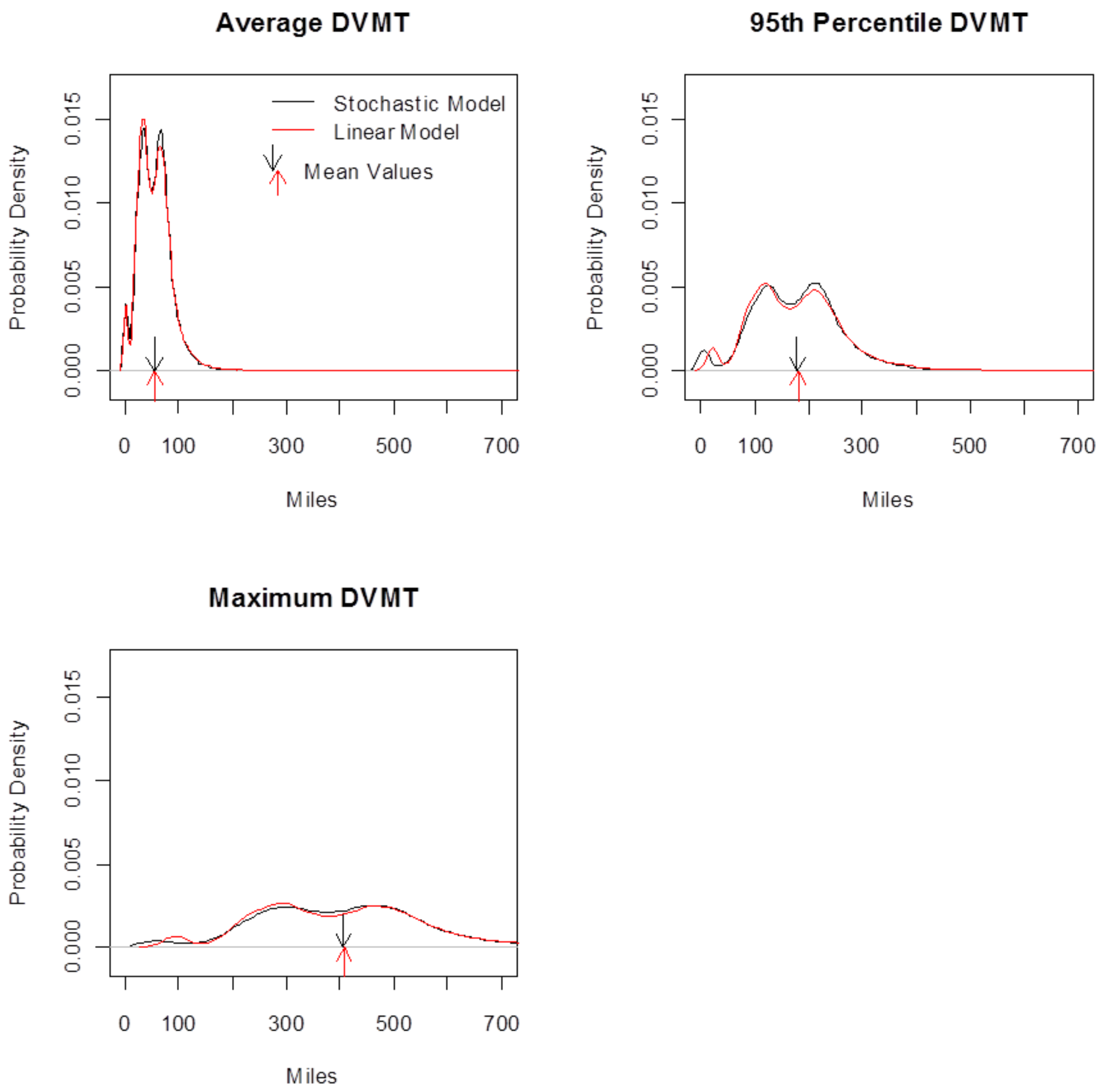


Figure 12: Comparison of Simulated and Estimated Distributions of Average DVMT, 95th Percentile DVMT, and Maximum DVMT for Non-Metropolitan Area Households



12 MODELING THE EFFECTS OF VEHICLE TRAVEL COSTS ON HOUSEHOLD VEHICLE TRAVEL

No costs are included in any of the household vehicle travel models. The effects of all variable vehicle costs (costs that vary with the amount of vehicle travel rather than with the number of vehicles owned) on travel are handled by a household travel budget model described in this section.

It is important that the FHWA tool 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. However, it is a challenging endeavor to account for the effects of prices on travel in a long-range model given:

- The lack of disaggregate panel data that can be used to study how household travel decisions change over time in response to changes in fuel prices;
- The relatively low historical price of fuel;
- The prospect for future fuel prices that may be several times greater than present prices;
- A lack of research consensus on the magnitude of the effects; and,
- The difficulty of sorting out short-range and long0range effects.

This section describes the approach for incorporating prices into the FHWA tool, 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).

12.1 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.[9] 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.[10]

The basic model concept is as follows:

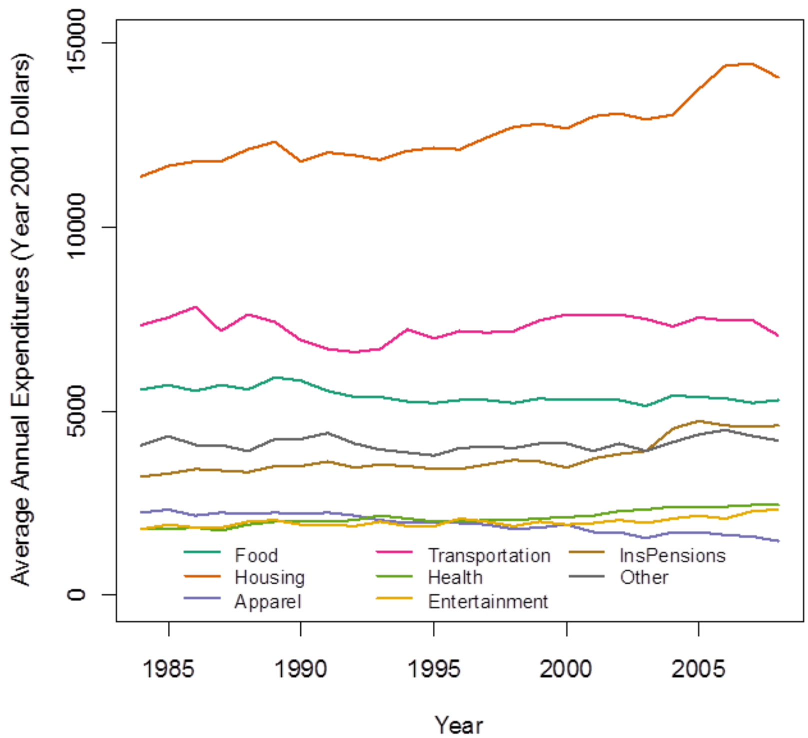
1. Household spending on gasoline and other variable costs is done within a household transportation budget that is relatively stable. Households shift expenses between transportation budget categories as needed.
2. As long as it is possible for the household to shift expenditures among components of 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 13 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.

[9] 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)

[10] 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 13: 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 14 shows trends in average annual household expenditures in these categories from 1984 to 2008 in real (2001) dollars.[11] 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 balancing of transportation expenditures can also be seen in Figure 15 which compares transportation expenditures for urban and rural households. The most significant aspect of this graph is that the higher gasoline expenditures of rural households are almost exactly offset by the lower expenditures on other vehicle expenses of these households.

[11] 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 14: Average Household Expenditures on Major Transportation Components, 1984-2008

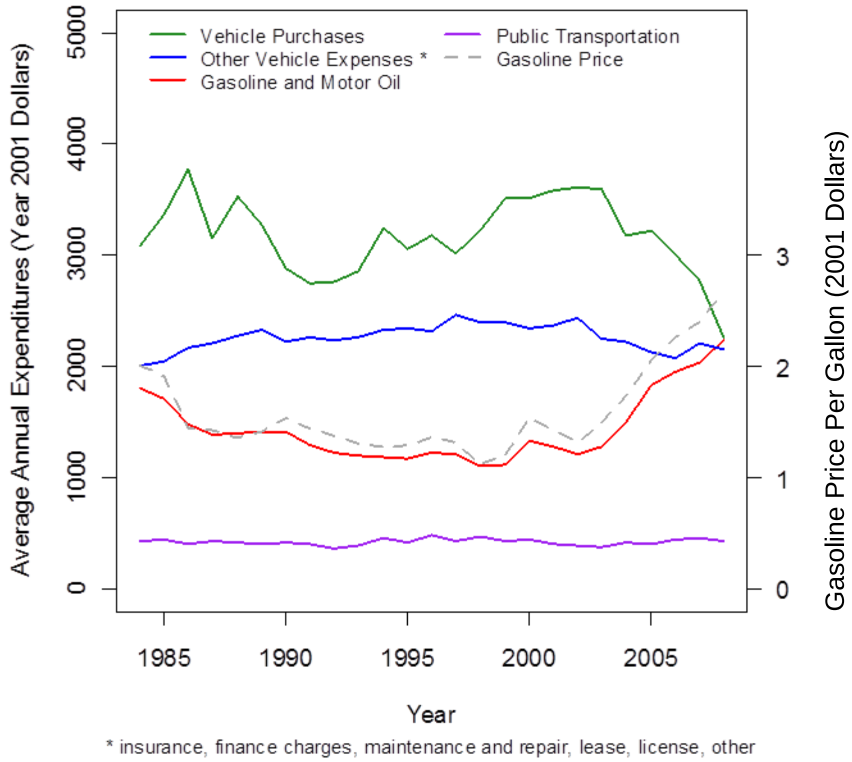
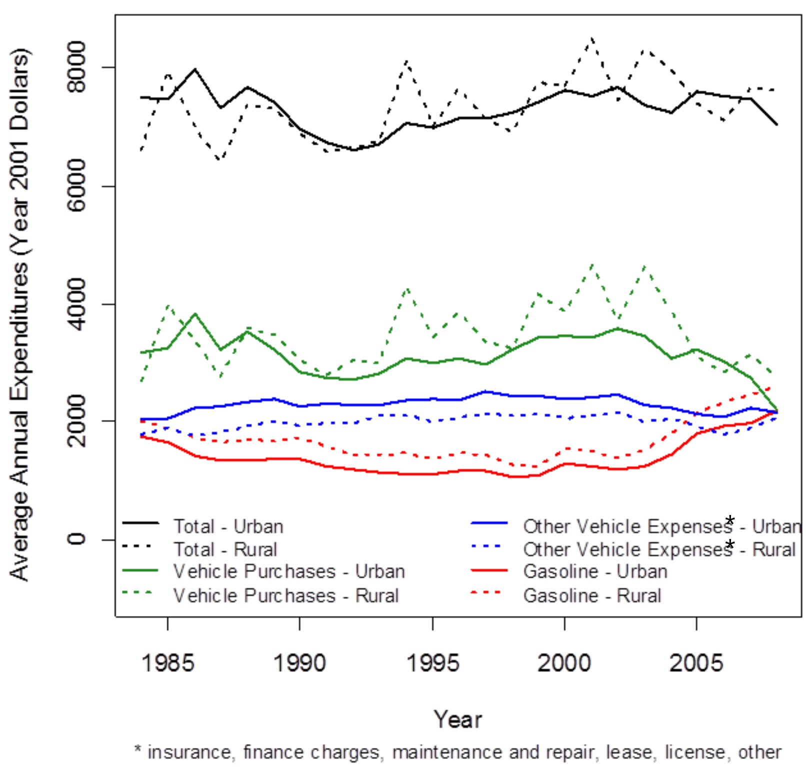


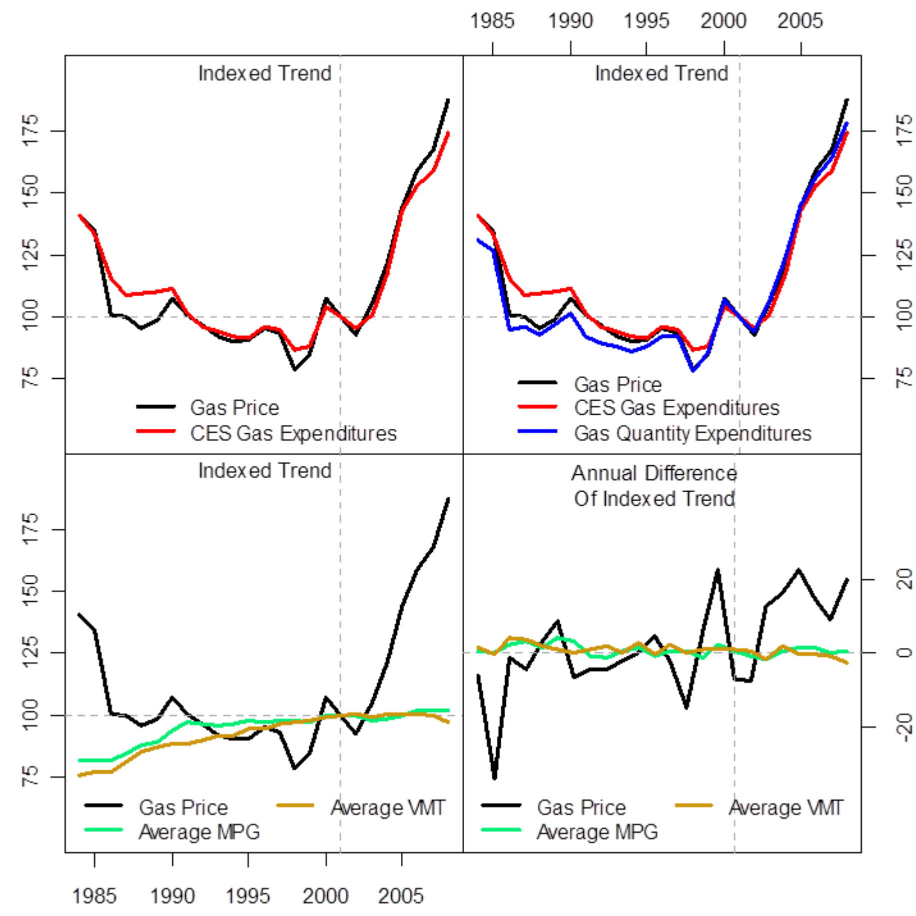
Figure 15: Comparison of Transportation Expenditures of Urban and Rural Households



The relationship between gasoline prices, household gasoline expenditures, and household vehicle travel is explored further in several graphs shown in Figure 16. 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. 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 16.

Figure 16: Trends in Gas Prices, Gas Quantity Expenditures, Average MPG, & Average VMT, Indexed to 2001 Values: 1984-2008



* Total quantity consumed divided by number of consuming units (see text)

Since the CES does not include information about fuel economy or miles of vehicle travel, we need to look for another source of information that relates 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 four-wheeled passenger vehicles. The latter type includes pickup trucks, sport utility vehicles (SUVs), 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 expenditures 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 16 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.

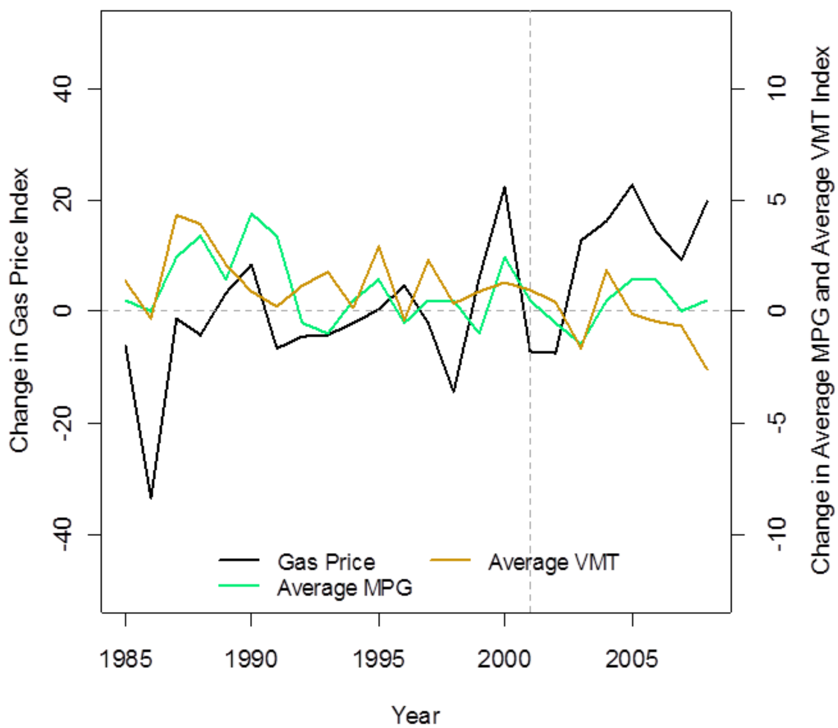
The lower left panel shows that changes in fuel economy and average household VMT were small relative to changes in fuel prices. Moreover, the directions of the fuel economy and VMT trends relative to fuel price trends imply that the trends may have been independent of one another. One would expect that 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 visa verse) 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 were no CAFE requirements 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.

VMT increased from year to year until 2008. 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 until 2007. Household VMT declined for the first time in 2008, but that arguably could have been caused by the major economic collapse that occurred in that year.

The lower right panel of Figure 16 shows year to year changes in the indexed values of gas prices, average 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 17, 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 those of MPG and VMT.

Figure 17: 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 is no longer 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 18 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 19 shows the same information disaggregated into more income categories at the top end. This data series starts at 2003 because before that incomes greater than $70,000 were lumped into one category.

Figure 18: Transportation Expenditures as a Percentage of Income, 1992-2008

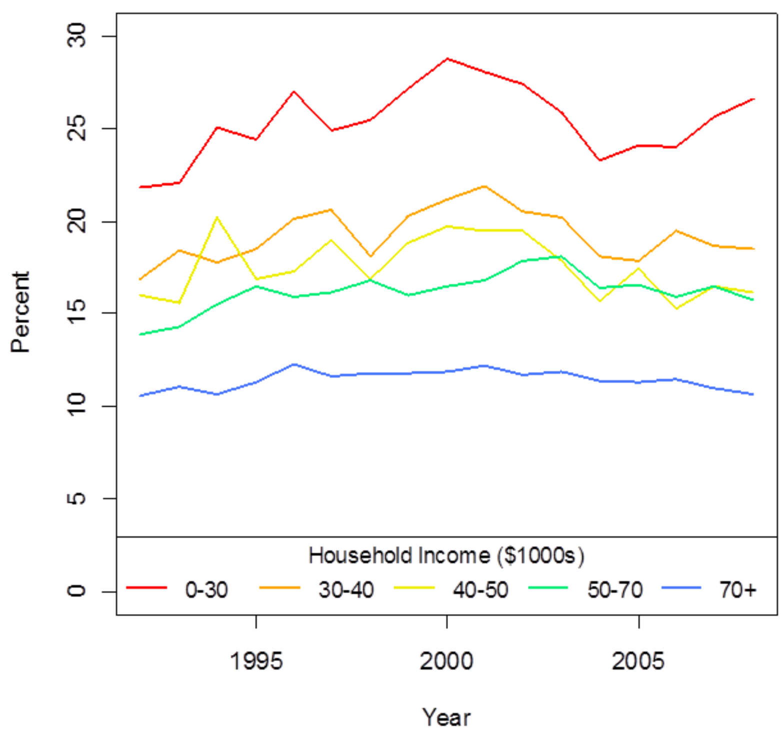
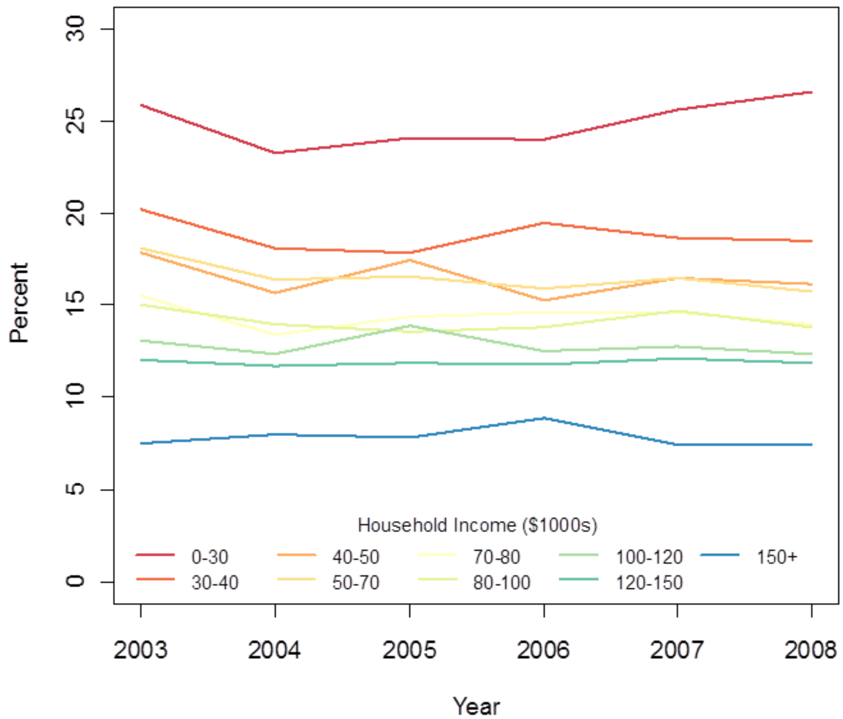


Figure 19: Transportation Expenditures as a Percentage of Income, 2003-2008



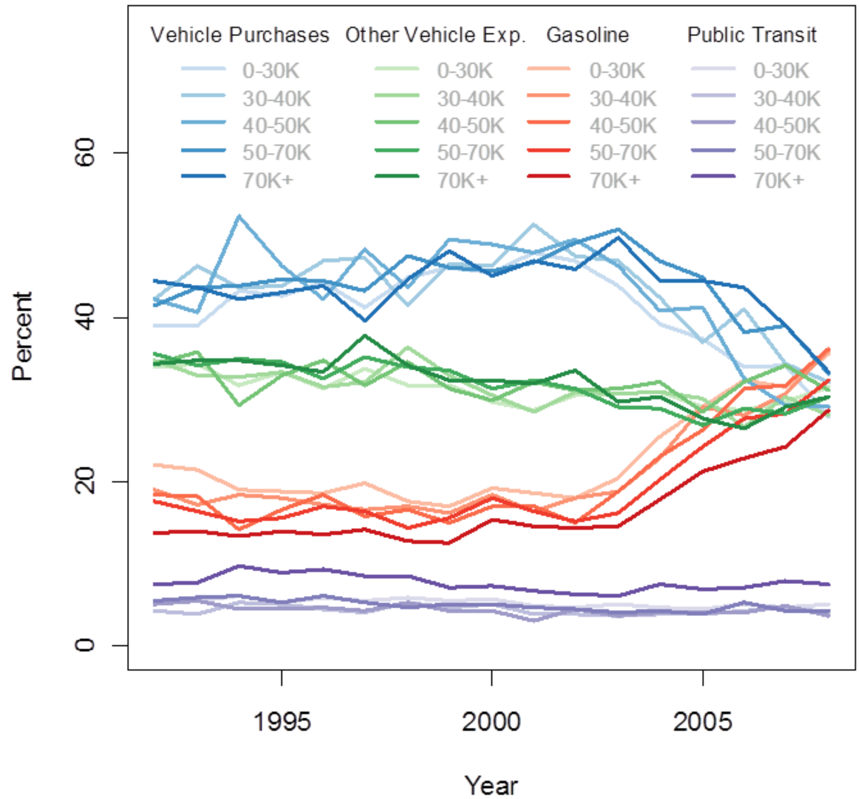
The figures show that the percentage of income consumed by transportation expenditures increases as household incomes decrease. This is to be expected since higher-income households save a higher percentage of their income. It is for this reason that higher-income household expenditure patterns should not be used in setting the transportation budget. It is better to use households having incomes low enough 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.[12] 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 1992-2008 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 20 shows the percentage of transportation expenditures spent on different budget categories by households having different incomes.

[12] http://www.bls.gov/cex/csxfaqs.htm#q20

Figure 20: Component Transportation Expenditures as a Percentage of Total Transportation Expenditures, 1992-2008

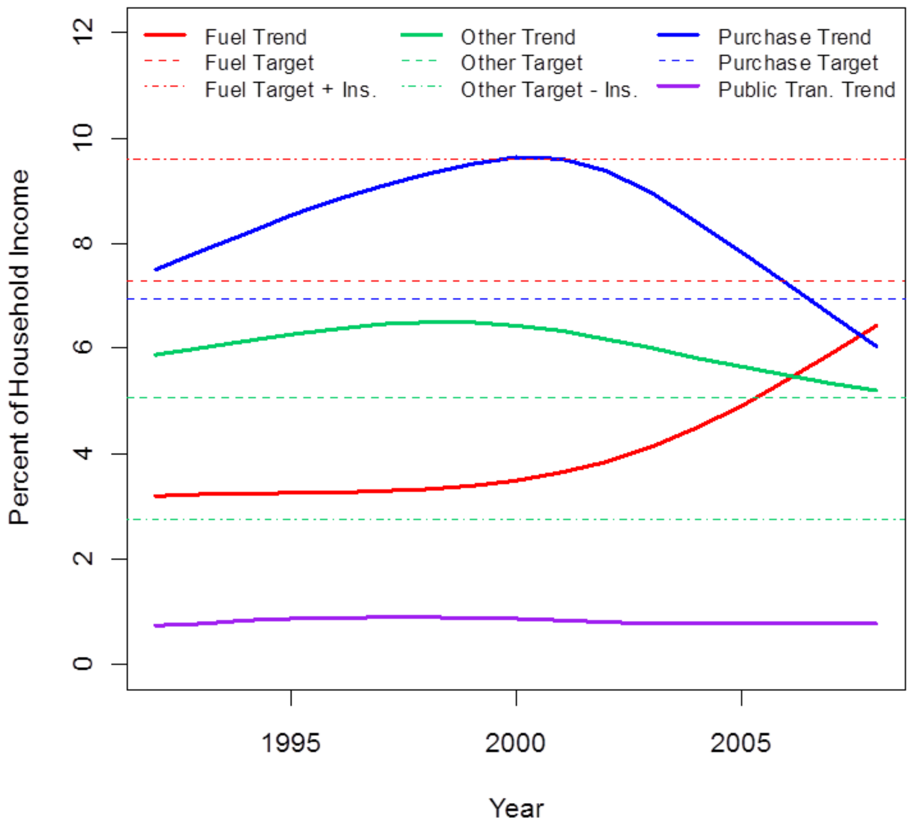


It can be seen that all income groups had very similar proportional splits of transportation expenses between the various categories. There are some noticeable differences though. Lower-income households tended to spend a higher percentage on gasoline and a lower percentage on vehicle purchases. The highest-income households spend a notably higher percentage on public transportation. This reflects air travel by these households. As before, the $30K to $40K 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 20 does not 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 21. 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 21: Annual Transportation Expenditure Trends for $30K to $40K Income Households and Initial Targets



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 21 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%.

12.2 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[13]). 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 22 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 36 and 37 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.

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

Figure 22: Illustration of Budget Functions and Transition Curves

Table 36: 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 37: 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 23 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 38 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 23: Comparing Model to CES Expenditures in 2001

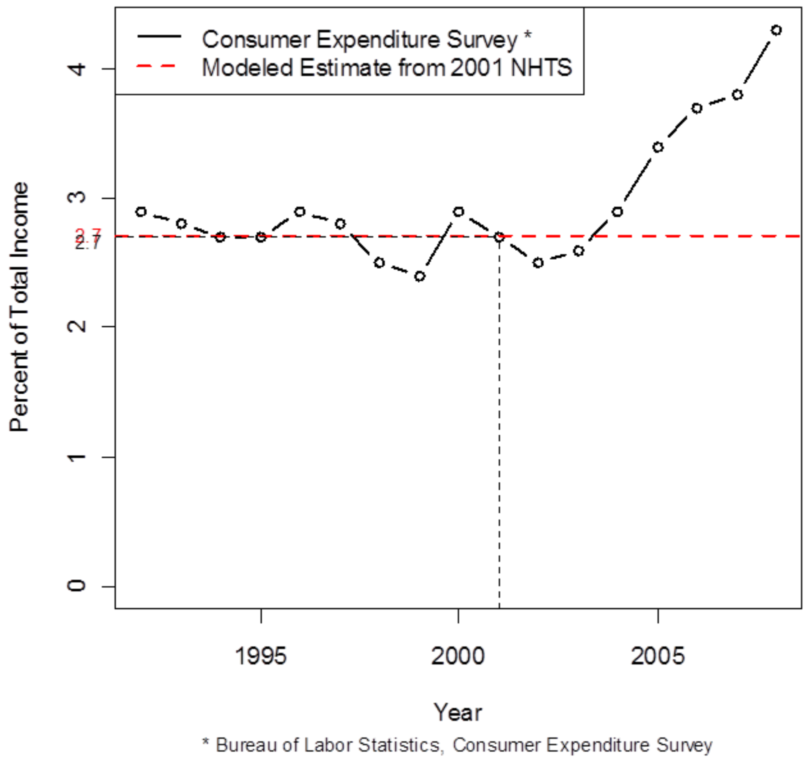


Table 38: Comparison of Model Estimated Household Gasoline Expenditures by Income Group in 2001 with Consumer Expenditure Survey Estimates

	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 24 and 25 show the results of these comparisons. 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.

Figure 24: Comparison of Model and CES Indexed Trends in the Proportions of Household Income Spent on Gasoline, 2001-2008, Transition Parameter = 0

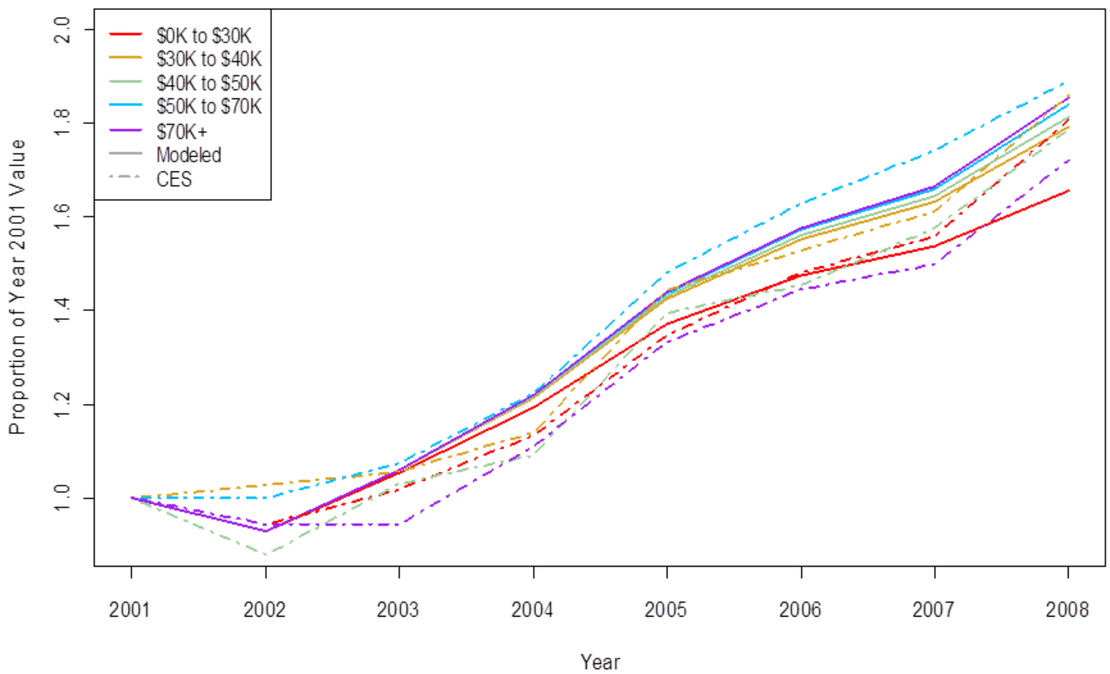
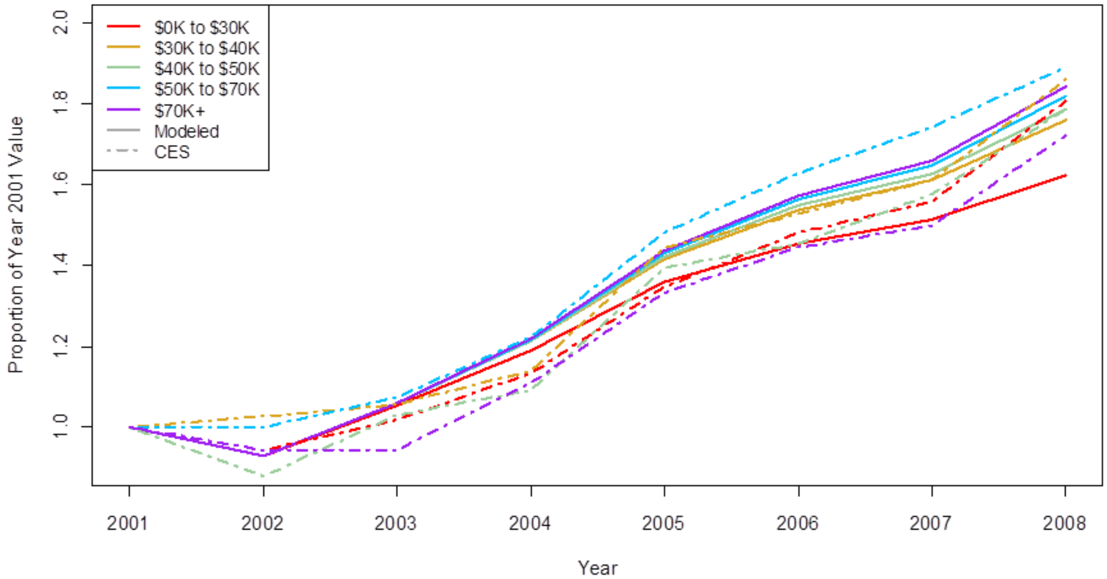


Figure 25: Comparison of Model and CES Indexed Trends in the Proportions of Household Income Spent on Gasoline, 2001-2008, Transition Parameter = 1



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.

13 MODELING TRAVEL DEMAND MANAGEMENT AND HOUSEHOLD VEHICLE OPERATIONS AND MAINTENANCE MEASURES

The FHWA tool models the effects of several travel demand management measures:

- Car-sharing
- PAYD insurance
- Fuel pricing
- VMT pricing
- Carbon pricing
- Parking pricing
- Employee commute options programs
- Individualized marketing programs.

Two types of household vehicle operations and maintenance measures are also modeled:

- Eco-driving
- Low rolling resistance tires.

13.1 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[14] and Martin and Shaheen,[15] and research documented by Millard-Ball[16] and the Victoria Transportation Policy Institute.[17]

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 to Martin and Shaheen's analysis of a survey of almost 10,000 car-sharing persons in North America, car-sharing 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 car-sharing households is synthesized. The basic approach is to develop weights for each key car-sharing attribute. Only three of the attributes listed above (car ownership, household size, and age of household members) are used. Household income is not used because the variable is continuous and no clear distinctions can be made for households participating in car-sharing. Educational attainment is not used because it is not modeled in the FHWA tool. Also, it is likely that the educational attainment characteristics of car-share households will change as car-sharing become more a prevalent and familiar service. Age is used in a simplified manner because like income it is

[14] 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.

[15] 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.

[16] 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.

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

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 in a Monte Carlo sampling process to choose households. Individual weights were determined in consideration of reported attributes of car-sharing households and iteratively adjusting weights so that at low car-sharing rates the vehicle and household size attributes of modeled car-sharing households are similar to the reported attributes. Table 39 shows the attribute weights used in the model. Values of attributes not shown in the table (e.g. households owning four vehicles) are assigned a weight of zero.

Table 39: Attribute Weights Used in the Model for Identifying Car-Sharing 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 car-sharing households is adjusted to reflect reductions in ownership documented by Martin and Shaheen with some simplifications. Table 40 shows the probabilities used in the model to adjust vehicle 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 car-sharing groups,[18] it is assumed that this was due to factors other than car-sharing. The probabilities shown in Table 40 are applied stochastically to adjust the number of cars owned by car-sharing 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.

The average household cost per mile for car-share 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 in the TDM Encyclopedia, the variable (per mile) cost of using a car-share vehicle is about 5 times more than the variable cost of using a privately owned vehicle.

Table 40: Car Ownership Probability for Car-Sharing Households by Number of Vehicles Owned Prior to Joining

Number of Cars	Probability of Number of Cars After Joining			
Prior to 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

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

The revised mileage cost for the car-share 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 car-sharing participants is calculated at 7.5 times the average gas cost per mile of households in the area. Table 41 shows the percentage of car-share households by number of vehicles owned before and after adjusting vehicle ownership. At the lowest rate of car-share participation, shown in the first row, the split of households among vehicle ownership groups is similar to the distribution reported by Martin and Shaheen (62% 0-veh., 31% 1-veh., 7% 2-veh.), and the after-adjustment distribution (80% 0-veh., 17% 1-veh., 3% 2-veh.).

Table 41: Before and After Split of Car-Share 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%

Table 42 shows how average vehicle ownership and DVMT changes for car-share households before and after vehicle adjustment. The average vehicle ownership rate at the lowest levels of car-share participation is similar to that reported by Martin, Shaheen and Lidicker (Before = 0.47, After = 0.24).[19] Martin et al. did not estimate the effect of car-share participation on household DVMT but this was done by Cervero, Golub and Nee with car-share survey data for the San Francisco Bay area.[20] Using survey data for car-share households and a set of similar households that were interested in joining car-sharing, they estimated a model of average household DVMT as a function of household and other characteristics. Their model predicted that, on average, participation in car-

[19] 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.

[20] 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

sharing reduced household DVMT by 7.08 miles. The average reduction predicted by the FHWA tool for the lowest participation level is 7.1 miles.

Table 42: Before and After Average Household DVMT of Car-Share 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 of car-sharing participation increases. This is consistent with the inclusion of larger households and households owning more vehicles in the car-sharing pool. This will happen if car-sharing grows beyond the niche it presently occupies.

13.2 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%.[21] The estimates of the effect of PAYD insurance is based on assumptions about the price elasticity of vehicle travel. The right value to use is uncertain.[22] Since the FHWA tool treats variable costs as a budget effect, price elasticity depends on the sum of all variable costs, therefore the estimated effect of PAYD insurance will depend on what other costs are being paid as well.

Table 43 shows the result of modeling PAYD insurance as a variable cost using the FHWA tool's budget approach. 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.

[21] 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.

[22] 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.

Table 43: 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

13.3 Fuel Pricing

Fuel prices are inputs to the model. The fuel cost per mile is calculated from those inputs. Increases to fuel prices due to market forces or to fuel taxes are accounted for in the fuel price inputs.

13.4 VMT Pricing

VMT pricing is a cost per vehicle mile traveled. Assumed costs are added in with other costs to determine the joint effect on travel.

13.5 Carbon Pricing

Carbon pricing is a charge on the production of CO_2 and other greenhouse gases created by the burning of carbon-based fuels (e.g. oil, coal, natural gas). Since the amount of GHG produced by transportation fuels is largely a function of the amounts of the fuels consumed and the carbon intensity of the fuels, any carbon price can be converted into an equivalent fuel cost per mile, which is added to the household's average gas cost per mile.

13.6 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. That is what is done in the FHWA tool, but 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 payment 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 who have to pay for parking at their place of work and the number who 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.

13.7 Employee Commute Options Programs and Individualized Marketing Programs

Employee commute options 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 programs are travel demand management programs focused on individual households. Individualized marketing 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 employee commute options programs and which participate in individualized marketing programs. The proportion of employees participating in employee commute options programs is a policy input. This is converted into a proportion of working age persons using an assumed labor force participation rate (0.65) to sample working age persons in households.

The sampling procedure for individualized marketing programs is more complicated because individualized marketing 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 individualized marketing program, assumptions are made about the minimum population density necessary to implement a successful individualized marketing 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 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).

The average DVMT of households is adjusted based on their participation in employee commute options and/or individualized marketing programs. The default assumption is that employee commute options programs reduce the average commute DVMT of participating households by 5.4%. This is based on assumptions used in the "Moving Cooler" study.[23] 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 employee commute options 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 individualized marketing program reduce their DVMT by 9% based on studies done in the Portland, OR area. Since individualized marketing programs target work as well as non-work travel and since individualized marketing programs produce larger reductions, only the individualized marketing reduction is used for households that are identified as participating in both employee commute options and individualized marketing programs.

13.8 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 FHWA tool, 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 fuel economy of the vehicles owned by 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.[24]

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

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

13.9 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 designated using a Monte Carlo process. The fuel economy of vehicles in these households is assumed to increase by 1.5%.[25]

14 VEHICLE FLEET MODELS

The Vehicle Fleet Models forecast the following characteristics of household vehicle fleets:

- Vehicle size type – auto vs. light truck
- Vehicle age by vehicle type and income group
- Allocation of household DVMT among vehicles
- EVs and PHEVs
- Non motorized vehicles, which includes electric bicycles
- Cost of vehicle fuel use, electric power use, VMT taxes, and carbon taxes.

The vehicle fleet models were estimated using records from the NHTS and are designed to calibrate to states' vehicle inventory (obtained from a state DMV). The Census region subset of the NHTS data in which the state is located is used for building the light truck and vehicle age models because light truck percentages and distribution of vehicle ages is significantly different by region of the country.

14.1 Vehicle Type Model

A light truck model was developed to determine which household vehicles, if any, would be light trucks. The model is built using the NHTS data for the Census region in which the state is located to have the model most closely match local conditions. In order to exactly match county level light truck proportions, the model was built to be self-calibrating so that it can match a specified truck proportion for each county in the state (which can be obtained from, for example, vehicle fleet characteristics in a MOVES model of the state in which the FHWA tool is being applied).

A binary logit model is used to predict vehicle type for each household vehicle. Table 44 shows the variable coefficients and statistics for the chosen model for the western Census region. 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

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

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 44: Light Truck Type Model (western Census region)

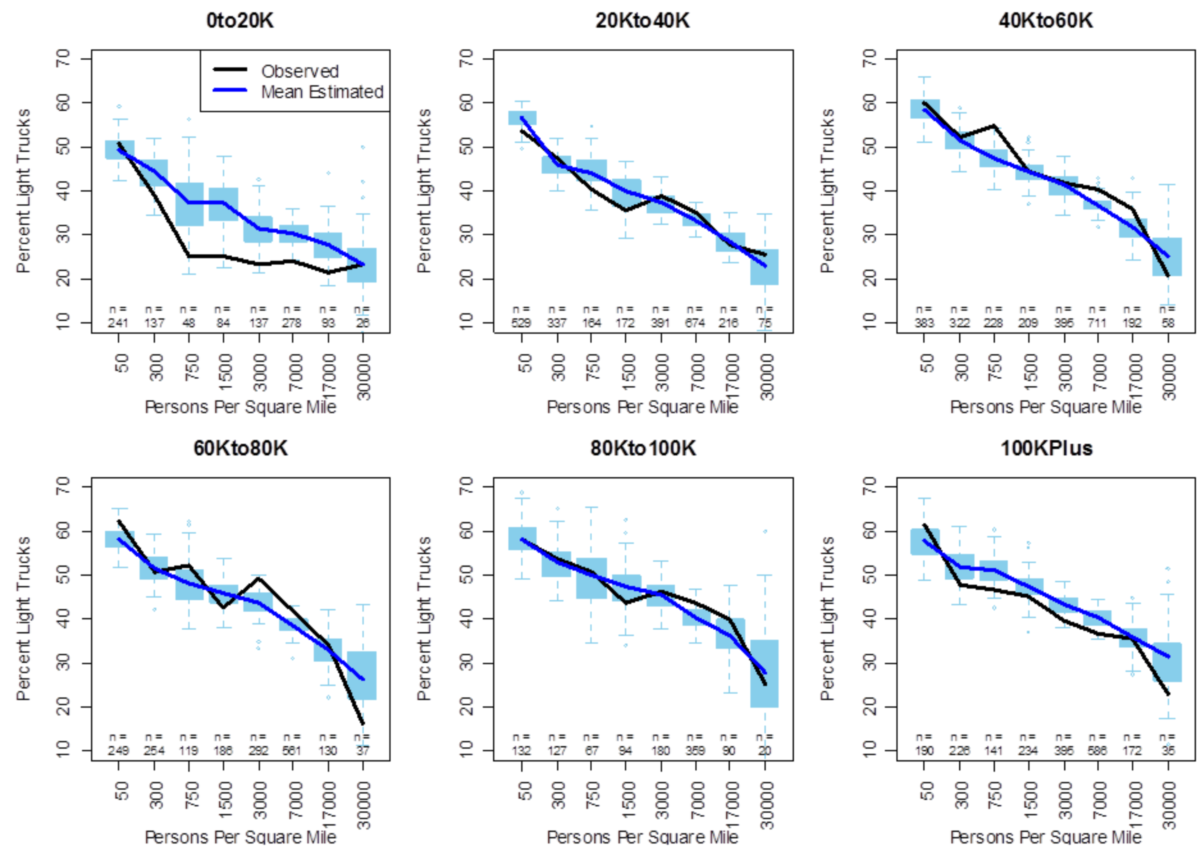
	Estimate	Std. Error	t value	Pr(>|t|)	
Hhincttl	0.00001062	0.000001312	8.089	6.02E-16	***
Hhvehcnt	0.3754	0.03118	12.039	<2e-16	***
Urban	-3.743	1.742	-2.148	0.031706	*
LogDen	-0.1737	0.0108	-16.075	<2e-16	***
Hhincttl:Hhvehcnt	-0.000003767	5.127E-07	-7.347	2.02E-13	***
Htppopdn:Hhvehcnt	0.000008775	0.000002422	3.623	0.000291	***
Htppopdn:Urban	-0.00005491	0.00001857	-2.957	0.003108	**
Urban:LogDen	0.4448	0.2114	2.104	0.035387	*

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05

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 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 26 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 26: Estimated and Observed Light Truck Ownership By Income Group and Density (100 model runs)



14.2 Vehicle Age Model

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 27. This responsiveness is important because vehicle age affects fuel economy, which affects fuel expenditures.

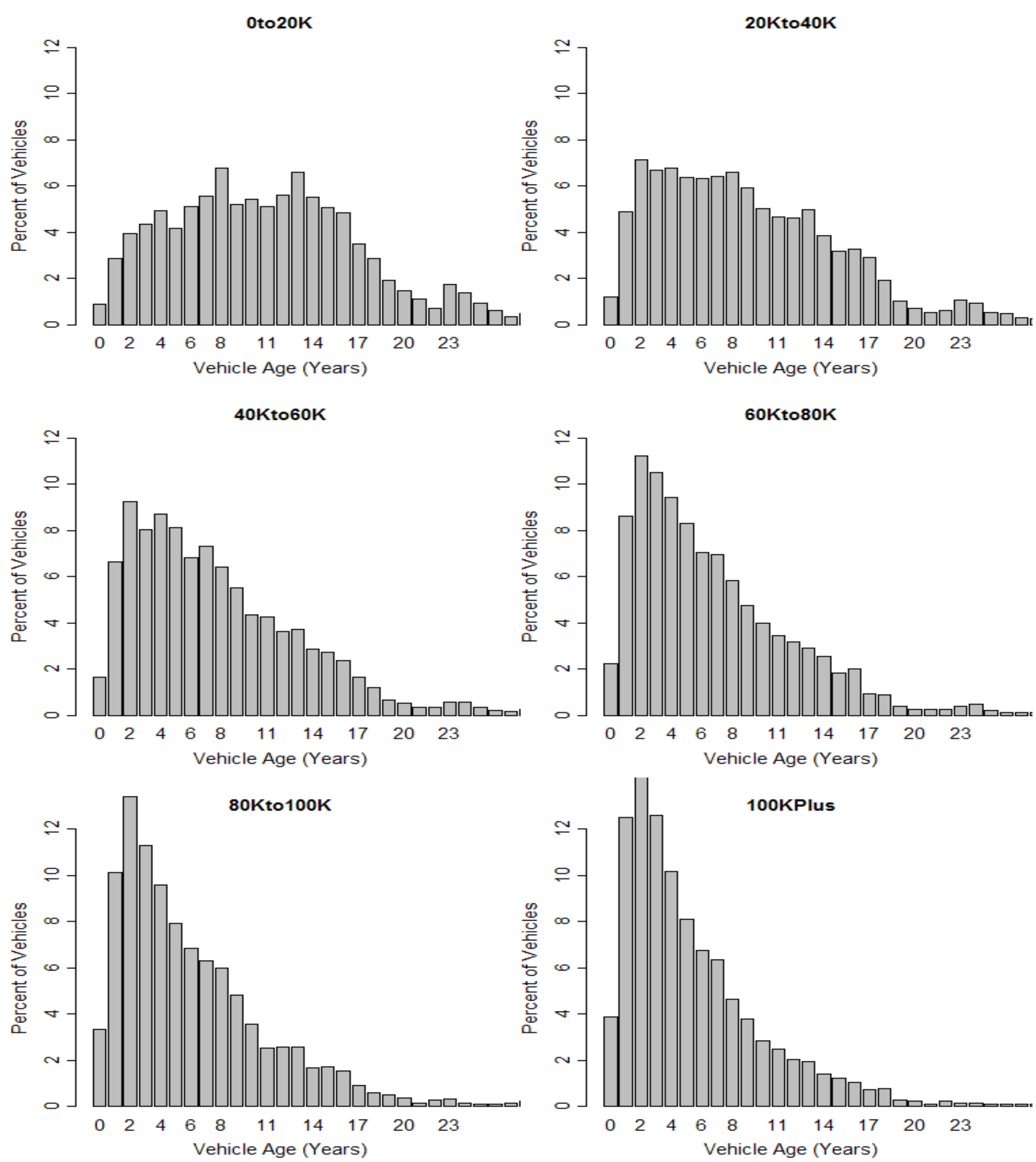
State DMV data generally does not include information about household income. Therefore, the Census region subset of the NHTS data is used to estimate this model for a state. The estimated model is then calibrated to match the state's vehicle age distribution.

The Census region subset of the NHTS 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 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 model in the FHWA tool uses a simple approach to model the vehicle age margin. Changes in the distribution of the ages of vehicles owned are 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 27: Vehicle Age Distribution by Household Income Group in Western Census Region Households



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 28 shows the results of running the auto vehicle age model 20 times for 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 29 shows the results for light trucks.

Figure 28: Observed and Estimated Auto Age Proportions By Income Group (20 model runs)

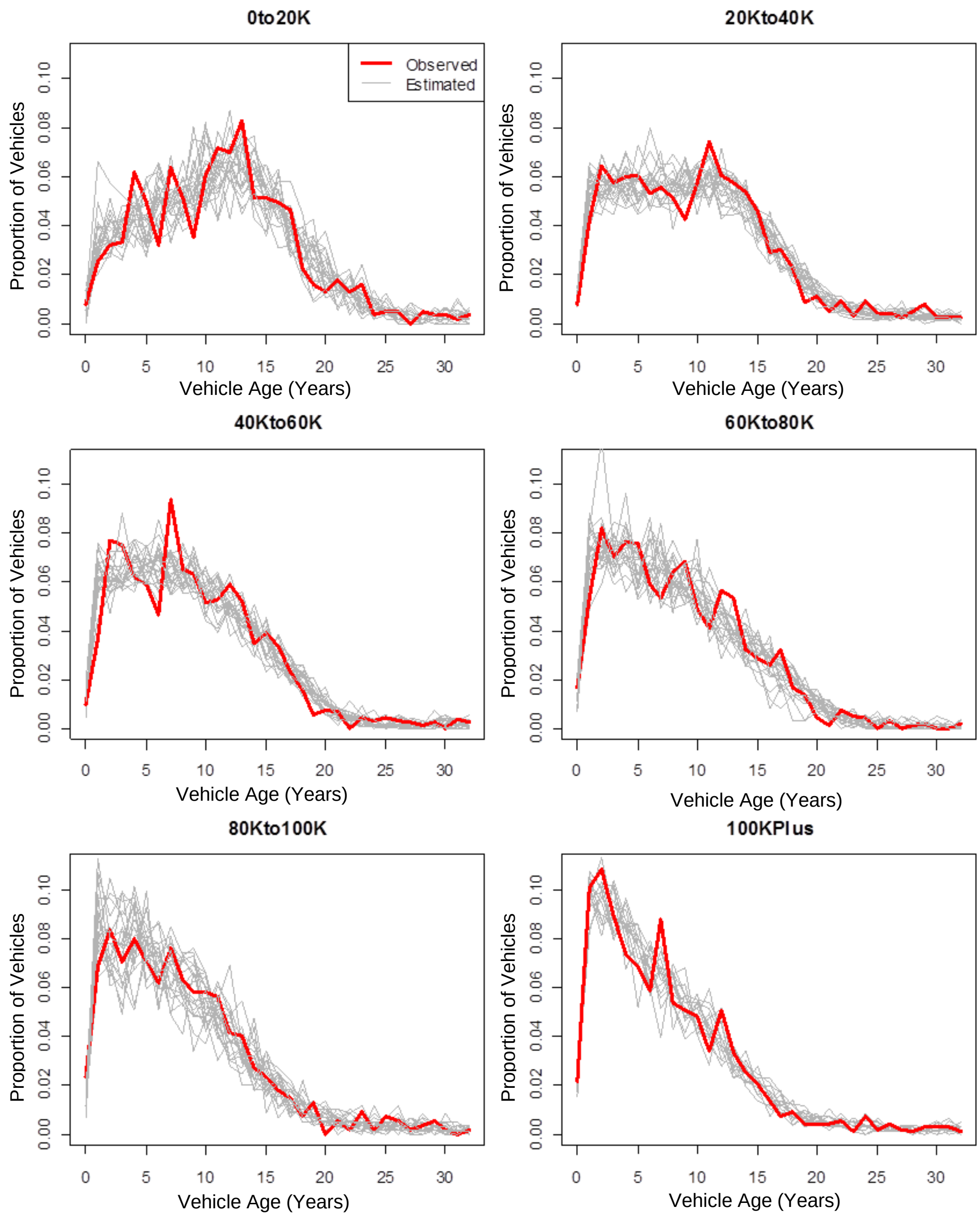
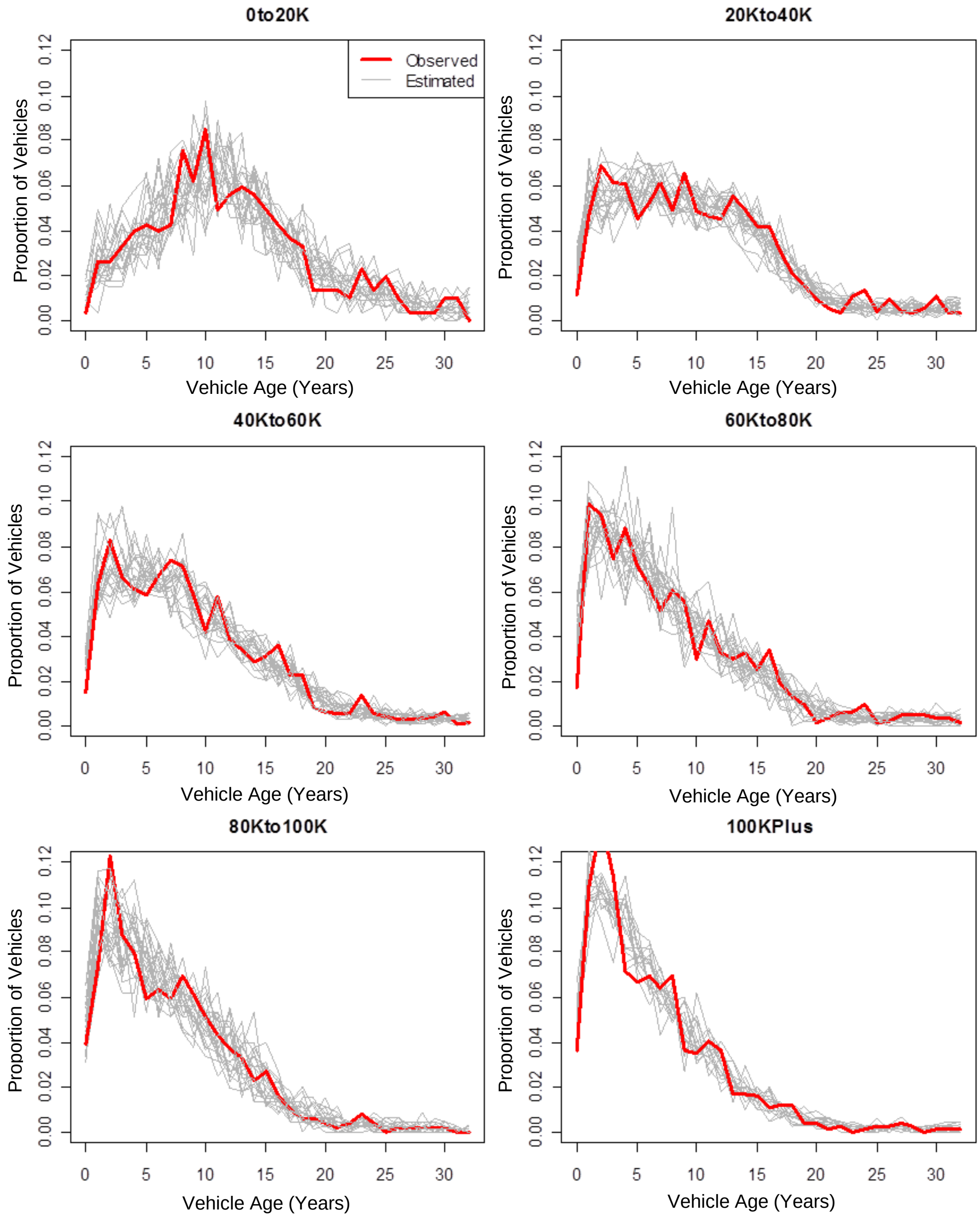


Figure 29: Observed and Estimated Light Truck Age Proportions By Income Group (20 model runs)



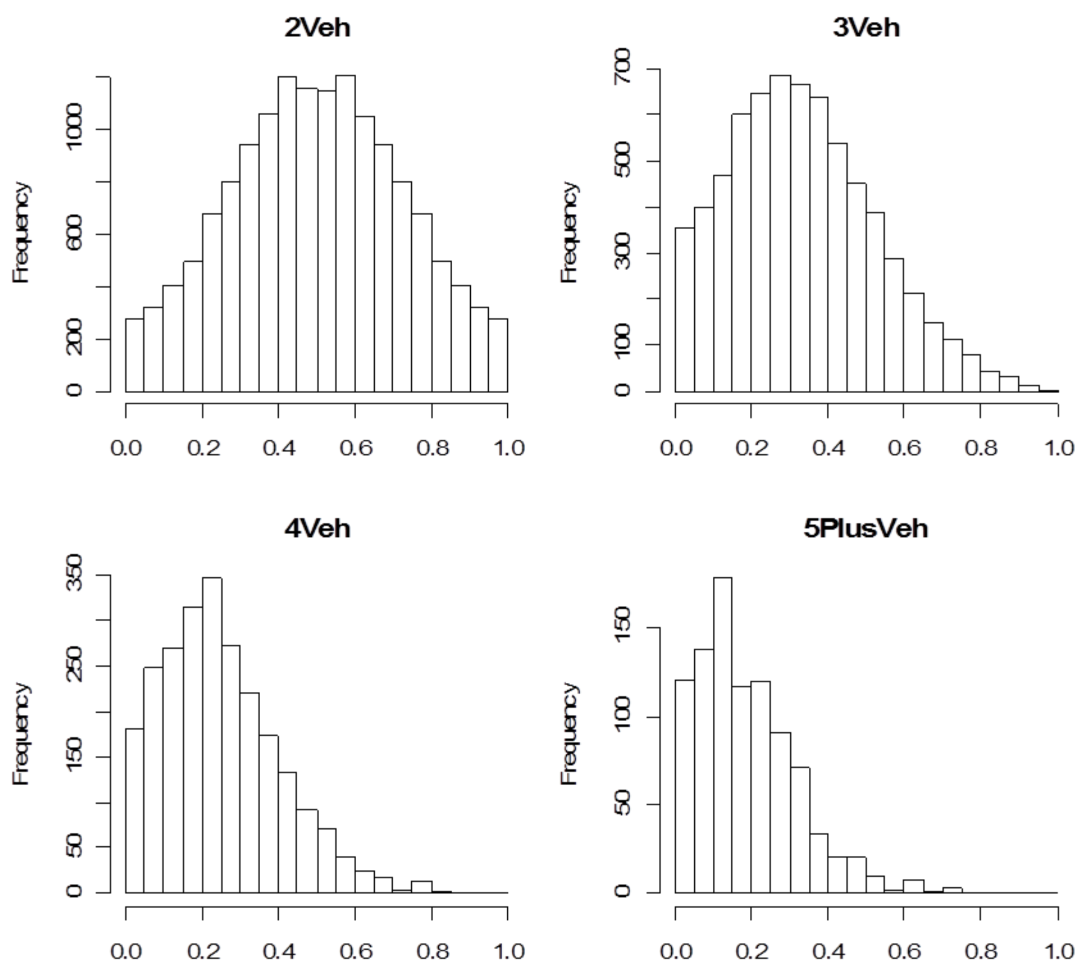
This approach to modeling vehicle fleet ages allows future scenarios to be specified easily. The 95th percentile age is used as a pivot point for adjusting the fleet age distribution. For example, if the model user inputs a value of 0.8, the 95th percentile age is adjusted to be 80 percent of the reference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

The joint distribution is calibrated to match the state fleet age distribution (which can be obtained from a MOVES model of the state in which the FHWA tool is being applied, or from the state DMV) by iterative proportional fitting. The estimated age margin is replaced by a distribution constructed by converting the smoothed cumulative age distribution for the state vehicle data. The matrix is rebalanced to create a joint distribution that reflects the age characteristics of the state vehicle fleet.

After each vehicle has been assigned a type (auto or light truck) and an age, it is assigned a fuel efficiency. The assigned value is the average fuel efficiency for the type and model year. Fuel efficiencies are the same for all fuel types and are measured in gasoline equivalent gallons (i.e. energy content of a gallon of gasoline). Past and current fuel efficiency values are as reported. Future values are a scenario input to the model.

The vehicle model also allocates household DVMT among the vehicles in the household. This is done by a Monte Carlo process using sampling distributions derived from data on annual miles traveled by vehicles in the survey data (Figure 30). The results are randomized so that there is no sampling order bias.

Figure 30: 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.

14.3 Plug-in Hybrid Electric Vehicle Model and Vehicle Use Optimization

The plug-in hybrid electric vehicle (PHEV) model has a simple allocation process for assigning PHEVs to households. The process for calculating the proportion of miles of travel powered by electricity is more complicated. Since PHEVs have an on-board engine, range is not a consideration affecting purchase. The FHWA tool assigns PHEV ownership using a simple Monte Carlo process where the choice probabilities are the assumed market penetration rates by vehicle type (car, light truck) and model year.

The model for estimating the proportion of PHEV mileage using electricity is more complicated, however. The approach used is based on the following assumptions:

1. All PHEVs in the future will have strong electric motors that enable the vehicle to operate on electricity over its entire speed range without assist subject only to the charge available in its batteries.[26]
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.
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 * 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.

[26] 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.

In order to model these values, it was necessary to develop distributions of vehicle travel by vehicle for each household. 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 Section 11. 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.

The combination of predicting household DVMT and proportioning the DVMT was run 400 times for each household to develop distributions of vehicle DVMT. Then, based on 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 FHWA tool, separate models were estimated for metropolitan and non-metropolitan households.

Figure 31 shows the coefficients for the metropolitan models. Figure 32 shows the corresponding coefficients for the non-metropolitan models. 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.

Figure 31: Coefficients of Metropolitan PHEV Electric Travel Proportions Models

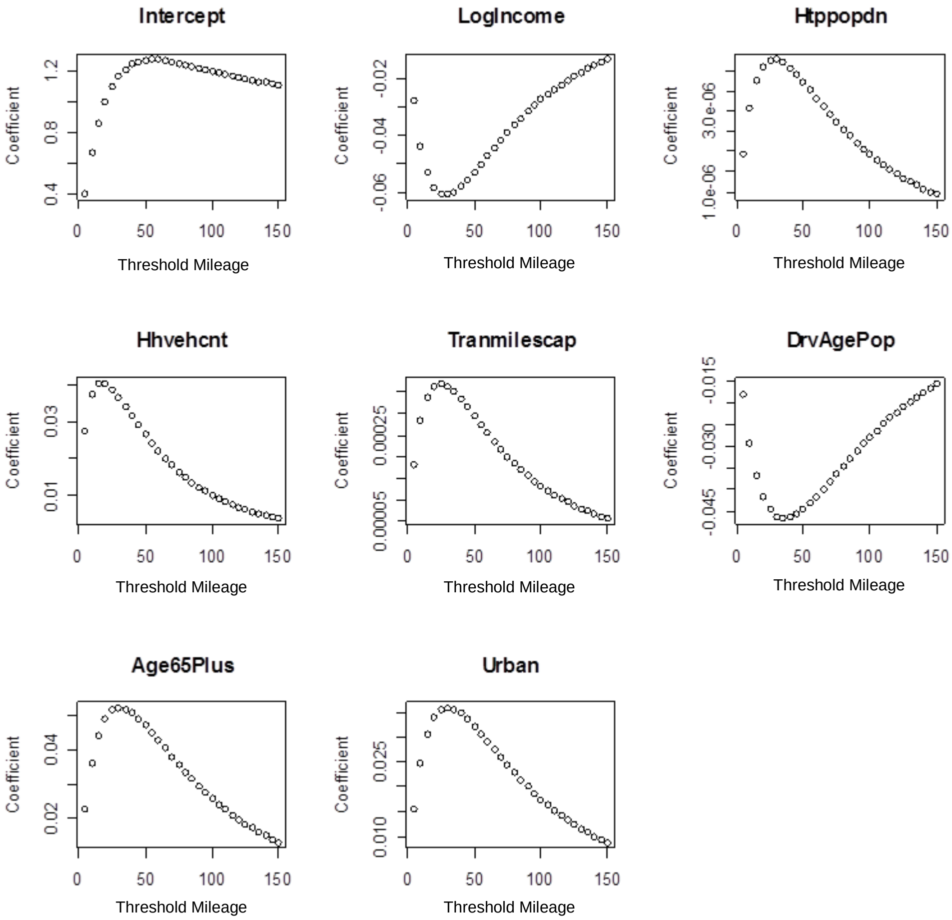


Figure 32: Coefficients of Non-Metropolitan PHEV Electric Travel Proportions Models

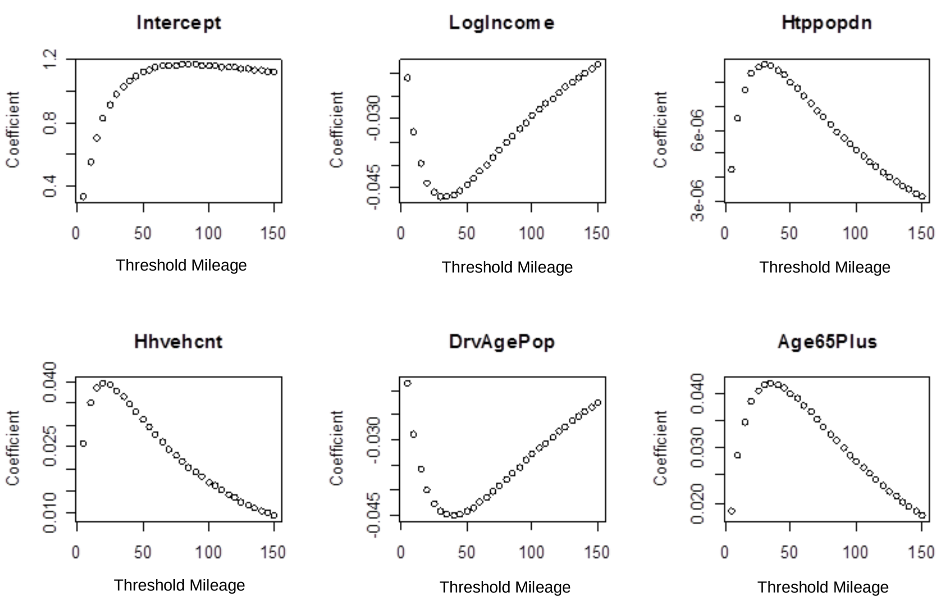
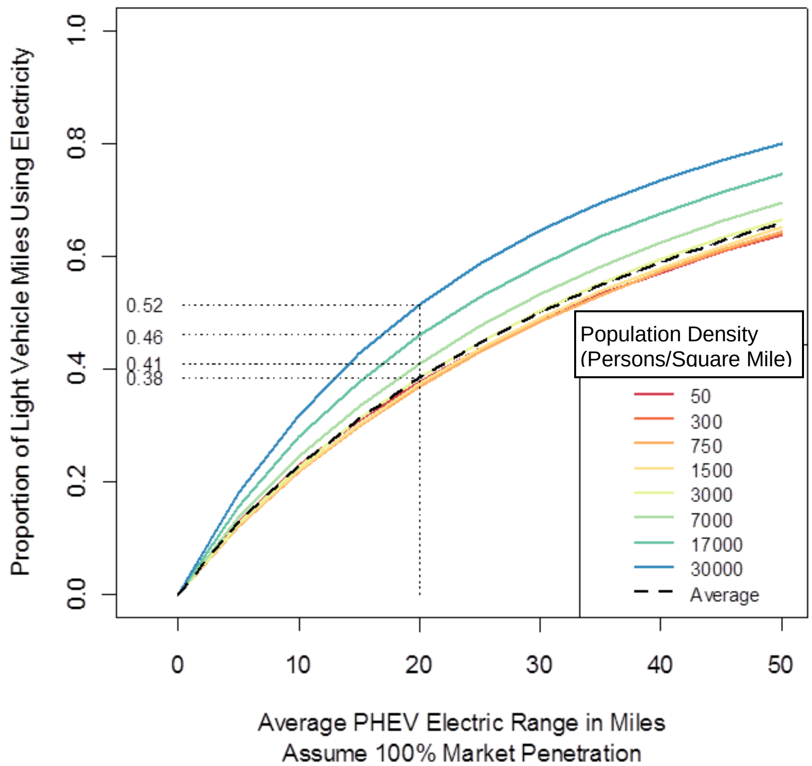


Figure 33 shows the results of testing the model using the metropolitan household data. As can be seen, the proportion of travel powered by stored electricity is sensitive to population density as well as the range of the vehicle. This model as well as the EV model will be sensitive to any factor that affects household DVMT.

Figure 33: Average Proportion of Travel Using Stored Electricity by PHEV Battery Range and Population Density Assuming 100% Market Penetration



Since PHEVs are hybrids, they have higher fuel economy than non-hybrid internal combustion engines. Therefore the fuel economy inputs for PHEVs are separate from the fuel economy inputs for other vehicles with internal combustion engines.

After PHEVs are assigned, the proportions of household DVMT allocated to different household vehicles is optimized. The proportion of households that are optimizers is an input that is used in a Monte Carlo process to identify optimizing households. For optimizing households, the proportion of household mileage put on each vehicle is ordered by the fuel economy of each vehicle. An equivalent fuel economy is calculated for PHEVs, which factors in the range of the PHEV battery and the energy efficiency of the electric drive train. The effect on overall fleet fuel efficiency varies with different optimization levels. In 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, optimization by all households reduces total fuel consumption by about 12 percent.

14.4 Electric Vehicle and Plug-in Hybrid Electric Vehicle Models

EVs will be an important technology for reducing GHG emissions from light vehicles. However, because EVs are a new technology, not much data are available to use for building a model. The potential for using EVs depends on the range that they can travel on a charge. The bigger the range, the larger the potential market for EVs. The potential for using EVs also depends on the amount of daily vehicle travel by households. The more travel that is done, the less likely an EV will be able to accommodate all of the travel. This interplay between EV range and household DVMT is important to capture in the model.

The approach taken in the FHWA tool 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 assumed EV range is sufficient to meet most of the vehicle needs. Vehicle designation as an EV also depends on the assumed rate of market penetration of EVs among candidate vehicles.

The candidate pool for EVs is the pool of PHEVs. This allows the effects of vehicles using electricity on travel costs, and thereby vehicle travel demand, to be modeled while avoiding a difficult process of finding a convergent solution that involves a very stochastic process. The variable cost a household faces is affected by whether the household uses an EV. Therefore, the modeling of household DVMT in response to cost should occur after EVs are assigned to households. However, the determination of whether a household is a candidate for an EV depends on the 95th percentile DVMT of each household vehicle. This suggests the need for iteration to get to a stable solution. However, the process is complicated by the stochastic nature of the EV model in which the households identified as owning EVs will change from iteration to iteration. By limiting the pool for candidate EVs to PHEVs we can approximate the cost of EV use by the cost of PHEV use, particularly if the battery range of PHEVs is moderately large. Then household DVMT can be modeled using those costs and EV allocation can follow.

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 are addressed in the development of the input assumptions to the EV model.

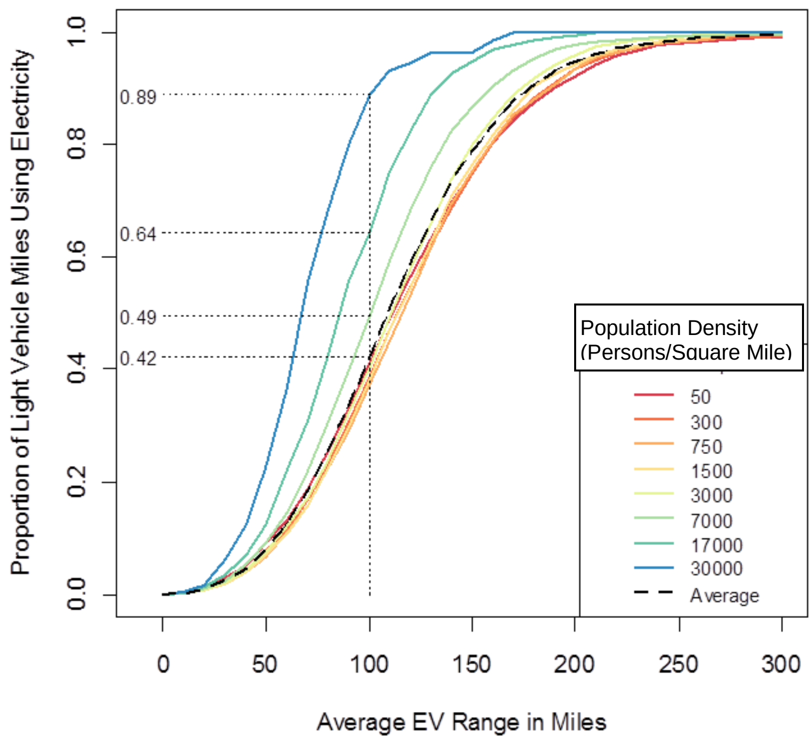
The determination of whether or not a household vehicle is an EV candidate is based on a comparison of the EV range with the 95th percentile DVMT for the vehicle. If the EV range is equal to or greater than the 95th percentile DVMT of a vehicle, then the vehicle is a candidate to be an EV. In other words, a household would consider owning an EV if it could meet all but 5% of their daily travel needs. The other 5% of the time might be accommodated by using other cars that the household owns and/or by replanning their activities to reduce how far they would travel.

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 percent of EV candidate vehicles 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 34 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 FHWA tool's approach accounts for those effects.

Figure 34: Travel Using Electricity by Average EV Range and Population Density Using 95th Percentile Criterion and Assuming 100% Market Penetration



15 NON-MOTORIZED VEHICLE MODEL

For the purposes of this documentation, non-motorized vehicles are bicycles, and also 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 non-motorized vehicle in use in the United States. This may well change as electric bicycles and other two-wheeled electric vehicles grow in market share. Two-wheeled electric vehicles have the potential for substantially increasing non-motorized 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 two-wheeled electric vehicles. Transportation system changes to accommodate non-motorized vehicles (e.g. adding bike lanes) are increasing the convenience and safety of non-motorized vehicle travel. These changes, along with increasing costs of gasoline and concerns about the impacts of vehicle travel could promote substantial increases in non-motorized 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.[27]

Modeling the potential future effect of non-motorized vehicles is a challenge because of limited information about how people will use two-wheeled electric vehicles in U.S. cities and how the use of non-motorized 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 non-motorized 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 non-motorized vehicles given a specified tour length threshold.

The other factors that determine the total household DVMT that is diverted to non-motorized travel are the proportion of households that have and use non-motorized vehicles and the proportion of SOV tours that non-motorized vehicles may be substituted for. A model is developed to predict the number of non-motorized 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 non-motorized vehicle ownership rate for the population. The proportion of SOV tours that non-motorized vehicles may be substituted for is a factor that reflects the effect of weather and trip purpose on limiting trips by non-motorized vehicles. This factor is multiplied by the potential DVMT that might be diverted by the household for households having non-motorized 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 were used to tabulate each household's vehicle travel occurring in SOV tours having lengths less than or equal to distance thresholds of 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.

[27] Joelle Garrus, Electric Bikes on a Roll in China, Agence France-Presse, 2/21/2010. http://www.google.com/hostednews/afp/article/ALeqM5iZWhbppjy_KtEwNap4PVgYg0bdDA

15.1 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 35. 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. Table 45 through Table 48 show the estimation results of the binomial models for predicting households doing no SOV travel for each mileage threshold. Table 49 through Table 52 show the estimation results of the binomial models for households doing all SOV travel for each mileage threshold. Table 53 through Table 56 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 35: Distribution of the Proportion of Household DVMT in SOV Tours

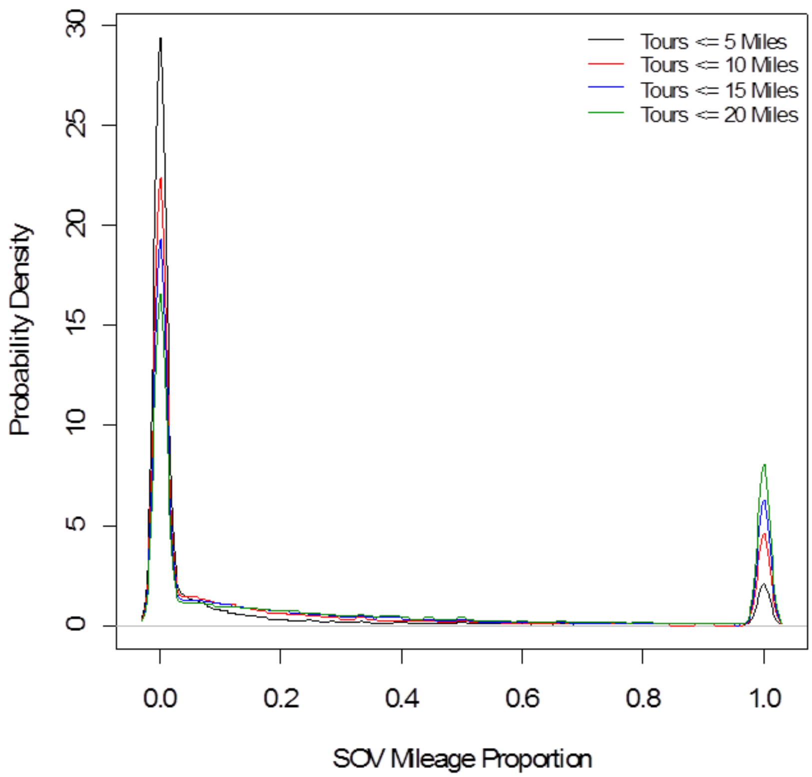


Table 45: Estimation Results for Binomial Model of Probability of No SOV Travel, Distance Threshold 5 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.33E+00	5.95E-02	-22.337	<2e-16	***
LogSize	1.38E+00	1.19E-01	11.66	<2e-16	***
Hhincttl	-1.54E-06	3.77E-07	-4.09	4.32E-05	***
Urban	-2.34E+00	5.06E-01	-4.614	3.94E-06	***
LogDvmt	9.16E-01	2.95E-02	31.038	<2e-16	***
LogDvmt:LogDen	-2.05E-02	3.57E-03	-5.753	8.79E-09	***
LogSize:LogDvmt	-3.59E-01	1.86E-02	-19.305	<2e-16	***
Urban:LogDvmt	6.80E-02	3.63E-02	1.876	0.0607	.
LogSize:LogDen	-5.92E-02	1.28E-02	-4.633	3.60E-06	***
Urban:LogDen	2.82E-01	5.22E-02	5.402	6.59E-08	***
Hhincttl:Urban	-2.82E-06	1.18E-06	-2.392	0.0167	*

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1
(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 46: Estimation Results for Binomial Model of Probability of No SOV Travel, Distance Threshold 10 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-2.26E+00	6.27E-02	-36.022	<2e-16	***
LogSize	1.69E+00	1.10E-01	15.312	<2e-16	***
Hhincttl	-2.98E-06	3.36E-07	-8.854	<2e-16	***
Urban	-3.46E+00	4.77E-01	-7.249	4.20E-13	***
LogDvmt	9.65E-01	2.61E-02	37.008	<2e-16	***
LogDvmt:LogDen	-2.66E-02	3.02E-03	-8.805	<2e-16	***
LogSize:LogDvmt	-4.28E-01	1.82E-02	-23.605	<2e-16	***
Urban:LogDvmt	1.08E-01	3.52E-02	3.067	0.002162	**
LogSize:LogDen	-4.15E-02	1.12E-02	-3.687	0.000227	***
Urban:LogDen	3.98E-01	4.85E-02	8.21	<2e-16	***
Hhincttl:Urban	-2.56E-06	1.09E-06	-2.355	0.018529	*

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05
(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 47: Estimation Results for Binomial Model of Probability of No SOV Travel, Distance Threshold 15 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-2.67E+00	6.52E-02	-40.961	<2e-16	***
LogSize	1.81E+00	1.10E-01	16.449	<2e-16	***
Hhincttl	-3.59E-06	3.33E-07	-10.779	<2e-16	***
Urban	-2.80E+00	4.47E-01	-6.275	3.50E-10	***
LogDvmt	9.50E-01	2.56E-02	37.098	<2e-16	***
LogDvmt:LogDen	-2.36E-02	2.85E-03	-8.292	<2e-16	***
LogSize:LogDvmt	-4.41E-01	1.85E-02	-23.815	<2e-16	***
LogSize:LogDen	-3.58E-02	1.09E-02	-3.287	0.00101	**
Urban:LogDen	3.63E-01	4.76E-02	7.614	2.65E-14	***
Hhincttl:Urban	-2.31E-06	1.05E-06	-2.209	0.02714	*

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05
(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 48: Estimation Results for Binomial Model of Probability of No SOV Travel, Distance Threshold 20 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-2.82E+00	7.99E-02	-35.246	<2e-16	***
LogSize	2.00E+00	1.13E-01	17.605	<2e-16	***
Hhincttl	-7.80E-06	1.20E-06	-6.485	8.88E-11	***
Urban	-2.50E+00	4.50E-01	-5.568	2.58E-08	***
LogDvmt	9.07E-01	2.80E-02	32.395	<2e-16	***
LogDvmt:LogDen	-2.39E-02	2.81E-03	-8.493	<2e-16	***
LogSize:LogDvmt	-4.92E-01	1.98E-02	-24.908	<2e-16	***
Hhincttl:LogDvmt	8.27E-07	3.05E-07	2.709	0.00676	**
LogSize:LogDen	-2.30E-02	1.08E-02	-2.121	0.03393	*
Urban:LogDen	3.17E-01	4.83E-02	6.567	5.14E-11	***

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05
(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 49: Estimation Results for Binomial Model of Probability of All Travel by SOV, Distance Threshold 5 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	6.82E+00	7.87E-01	8.672	<2e-16	***
LogDen	3.12E-01	1.03E-01	3.024	0.00249	**
LogSize	-3.10E+00	3.58E-01	-8.66	<2e-16	***
Hhincttl	3.89E-06	1.74E-06	2.239	0.02517	*
LogDvmt	-3.10E+00	3.89E-01	-7.964	1.67E-15	***
LogDen:LogDvmt	-2.04E-01	5.12E-02	-3.977	6.97E-05	***
LogSize:LogDvmt	9.81E-01	1.78E-01	5.509	3.60E-08	***

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05
(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 50: Estimation Results for Binomial Model of Probability of All Travel by SOV, Distance Threshold 10 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	8.95E+00	2.94E-01	30.42	<2e-16	***
LogSize	-3.42E+00	2.54E-01	-13.476	<2e-16	***
Hhincttl	1.60E-05	4.48E-06	3.563	0.000367	***
LogDvmt	-3.33E+00	1.10E-01	-30.188	<2e-16	***
LogSize:LogDvmt	7.97E-01	9.63E-02	8.275	<2e-16	***
Hhincttl:LogDvmt	-5.22E-06	1.67E-06	-3.137	0.001708	**

Signif. codes: 0 *** 0.001 ** 0.01
(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 51: Estimation Results for Binomial Model of Probability of All Travel by SOV, Distance Threshold 15 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	9.85E+00	5.68E-01	17.342	<2e-16	***
LogDen	-1.69E-01	7.01E-02	-2.414	0.0158	*
LogSize	-2.84E+00	3.24E-01	-8.757	<2e-16	***
Hhincttl	1.76E-05	3.76E-06	4.677	2.91E-06	***
LogDvmt	-3.33E+00	1.81E-01	-18.429	<2e-16	***
LogDen:LogDvmt	6.48E-02	2.23E-02	2.913	0.00358	**
LogSize:LogDvmt	6.77E-01	7.55E-02	8.956	<2e-16	***
Hhincttl:LogDvmt	-5.10E-06	1.26E-06	-4.064	4.82E-05	***
LogDen:LogSize	-8.48E-02	3.05E-02	-2.784	0.00537	**
LogSize:Urban	4.14E-01	1.49E-01	2.778	0.00546	**
Hhincttl:Urban	-4.21E-06	1.95E-06	-2.159	0.03086	*

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05
(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 52: Estimation Results for Binomial Model of Probability of All Travel by SOV, Distance Threshold 20 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	9.98E+00	4.88E-01	20.461	<2e-16	***
LogDen	-2.69E-01	5.94E-02	-4.525	6.05E-06	***
LogSize	-2.83E+00	2.81E-01	-10.1	<2e-16	***
Hhincttl	1.62E-05	3.16E-06	5.139	2.76E-07	***
LogDvmt	-2.99E+00	1.43E-01	-20.879	<2e-16	***
LogDen:LogDvmt	8.02E-02	1.75E-02	4.588	4.48E-06	***
LogSize:LogDvmt	5.69E-01	6.14E-02	9.267	<2e-16	***
Hhincttl:LogDvmt	-4.70E-06	9.83E-07	-4.783	1.72E-06	***
LogDen:LogSize	-6.66E-02	2.52E-02	-2.649	0.00807	**
LogSize:Urban	2.39E-01	8.57E-02	2.791	0.00526	**

Signif. codes: 0 *** 0.001 ** 0.01
(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 53: Estimation Results for Linear Model of the Proportion of Household DVMT in SOV Tours <= 5 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	4.94E-01	2.16E-02	22.886	<2e-16	***
LogDen	1.94E-02	2.66E-03	7.282	3.54E-13	***
LogSize	-3.82E-02	9.42E-03	-4.05	5.15E-05	***
Hhincttl	-4.95E-07	1.49E-07	-3.329	0.000874	***
Urban	-1.59E-02	4.32E-03	-3.673	0.000241	***
LogDvmt	-1.10E-01	5.78E-03	-19.095	<2e-16	***
LogDen:LogDvmt	-4.80E-03	6.93E-04	-6.933	4.37E-12	***
LogSize:LogDvmt	1.76E-02	2.60E-03	6.752	1.54E-11	***
Hhincttl:LogDvmt	2.27E-07	3.85E-08	5.891	3.96E-09	***
LogSize:Hhincttl	-2.72E-07	7.53E-08	-3.616	0.000301	***

Signif. codes: 0 *** 0.001
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 54: Estimation Results for Linear Model of the Proportion of Household DVMT in SOV Tours <= 10 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	5.42E-01	2.45E-02	22.123	<2e-16	***
LogDen	2.48E-02	3.35E-03	7.413	1.30E-13	***
LogSize	2.40E-02	5.01E-03	4.777	1.79E-06	***
Urban	1.83E-01	5.78E-02	3.16	0.001583	**
LogDvmt	-1.06E-01	6.20E-03	-17.154	<2e-16	***
LogDen:LogDvmt	-5.38E-03	8.39E-04	-6.408	1.52E-10	***
LogDvmt:Hhincttl	1.02E-07	2.13E-08	4.773	1.83E-06	***
LogSize:Hhincttl	-1.83E-07	7.93E-08	-2.302	0.021374	*
LogDen:Urban	-2.27E-02	6.30E-03	-3.609	0.000309	***

Signif. codes: 0‘*** 0.001 ** 0.01 * 0.05
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 55: Estimation Results for Linear Model of the Proportion of Household DVMT in SOV Tours <= 15 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	6.10E-01	2.94E-02	20.74	<2e-16	***
LogDen	1.81E-02	3.81E-03	4.752	2.03E-06	***
LogSize	1.79E-02	2.97E-03	6.051	1.47E-09	***
Hhincttl	9.24E-07	1.94E-07	4.763	1.92E-06	***
Urban	2.46E-01	6.58E-02	3.734	0.000189	***
LogDvmt	-1.11E-01	7.24E-03	-15.382	<2e-16	***
LogDen:LogDvmt	-3.82E-03	9.41E-04	-4.056	5.02E-05	***
Hhincttl:LogDvmt	-1.47E-07	4.84E-08	-3.038	0.002389	**
LogDen:Urban	-2.81E-02	7.16E-03	-3.926	8.66E-05	***

Signif. codes: 0 *** 0.001 ** 0.01
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 56: Estimation Results for Linear Model of the Proportion of Household DVMT in SOV Tours <= 20 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	6.84E-01	2.06E-02	33.227	<2e-16	***
LogDen	7.42E-03	1.79E-03	4.143	3.44E-05	***
LogSize	2.70E-02	3.26E-03	8.284	<2e-16	***
Hhincttl	2.12E-06	3.09E-07	6.852	7.53E-12	***
Urban	2.49E-01	7.42E-02	3.36	0.00078	***
LogDvmt	-1.29E-01	3.70E-03	-34.837	<2e-16	***
Hhincttl:LogDvmt	-3.00E-07	5.38E-08	-5.574	2.52E-08	***
LogDen:Hhincttl	-7.83E-08	2.67E-08	-2.935	0.003344	**
LogDen:Urban	-2.79E-02	8.06E-03	-3.465	0.000531	***

Signif. codes: 0 *** 0.001 ** 0.01
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

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 36 shows the distributions of the resulting estimates. The means of the estimated average values are very close to the means of the observed values. Once the average proportions had been calculated for each household through simulation, linear models were estimated to predict the averages. Table 57 through Table 60 show the estimation statistics for the models.

Figure 36: Distribution of the Average Proportions of Household DVMT in SOV Tours by Maximum Tour Length

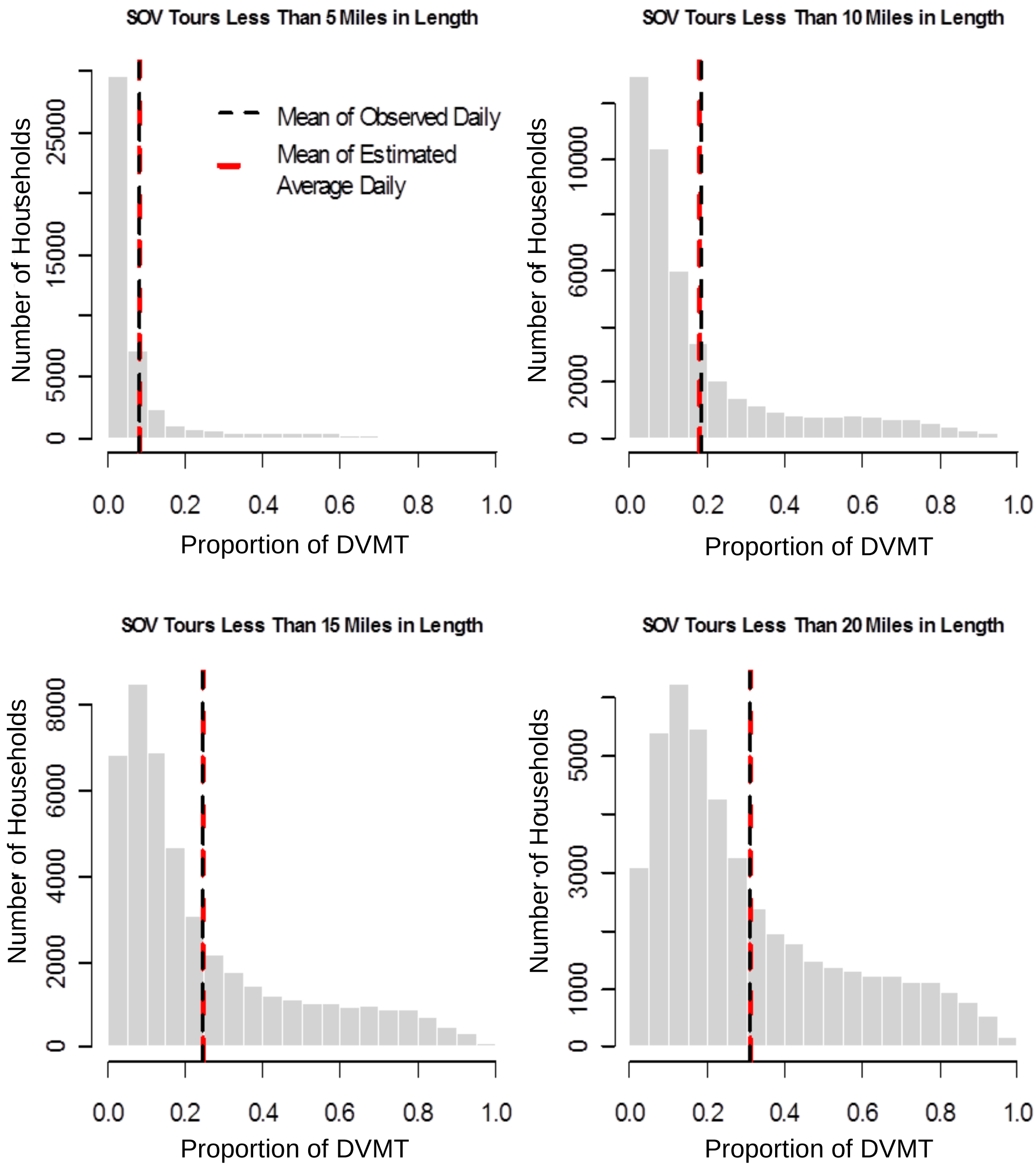


Table 57: **Estimation Results for Linear Model of the Proportion of Household DVMT in SOV Tours <= 5 Miles**

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	5.32E-01	4.98E-03	106.689	<2e-16	***
Hhincttl	-1.25E-06	6.20E-08	-20.113	<2e-16	***
LogDen	1.92E-02	6.38E-04	30.046	<2e-16	***
LogSize	-2.65E-01	3.63E-03	-73.155	<2e-16	***
Urban	8.88E-02	1.45E-02	6.116	9.65E-10	***
LogDvmt	-1.22E-01	1.27E-03	-96.089	<2e-16	***
Hhincttl:LogDvmt	3.92E-07	9.43E-09	41.509	<2e-16	***
LogDen:LogDvmt	-7.40E-03	1.62E-04	-45.6	<2e-16	***
LogSize:LogDvmt	6.49E-02	5.83E-04	111.268	<2e-16	***
Hhincttl:LogDen	4.26E-08	6.46E-09	6.59	4.46E-11	***
Hhincttl:LogSize	-3.88E-07	2.13E-08	-18.2	<2e-16	***
Hhincttl:Urban	2.95E-07	3.75E-08	7.861	3.89E-15	***
LogDen:LogSize	7.32E-03	3.71E-04	19.725	<2e-16	***
LogDen:Urban	-1.33E-02	1.55E-03	-8.581	<2e-16	***

Signif. codes: 0 *** 0.001
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 58: Estimation Results for Linear Model of the Proportion of Household DVMT in SOV Tours <= 10 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	7.79E-01	5.14E-03	151.625	<2e-16	***
Hhincttl	-1.54E-07	6.23E-08	-2.471	0.013473	*
LogDen	3.30E-02	6.74E-04	49.019	<2e-16	***
LogSize	-3.59E-01	3.74E-03	-96.038	<2e-16	***
Urban	3.32E-01	1.51E-02	22.007	<2e-16	***
LogDvmt	-1.79E-01	1.34E-03	-133.802	<2e-16	***
Hhincttl:LogDvmt	1.59E-07	9.45E-09	16.764	<2e-16	***
LogDen:LogDvmt	-8.19E-03	1.79E-04	-45.706	<2e-16	***
LogSize:LogDvmt	8.62E-02	5.85E-04	147.472	<2e-16	***
Urban:LogDvmt	4.19E-03	1.16E-03	3.624	0.000291	***
Hhincttl:LogDen	1.48E-08	6.54E-09	2.269	0.023262	*
Hhincttl:LogSize	-2.41E-07	2.14E-08	-11.256	<2e-16	***
Hhincttl:Urban	3.66E-07	3.95E-08	9.257	<2e-16	***
LogDen:LogSize	4.35E-03	4.08E-04	10.673	<2e-16	***
LogDen:Urban	-4.48E-02	1.56E-03	-28.773	<2e-16	***
LogSize:Urban	5.09E-03	2.50E-03	2.04	0.041336	*

Signif. codes: 0 *** 0.001 ** 0.01* 0.05
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 59: Estimation Results for Linear Model of the Proportion of Household DVMT in SOV Tours <= 15 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	9.36E-01	4.69E-03	199.893	<2e-16	***
Hhincttl	7.01E-07	3.42E-08	20.483	<2e-16	***
LogDen	2.74E-02	6.17E-04	44.444	<2e-16	***
LogSize	-3.66E-01	2.02E-03	-180.792	<2e-16	***
Urban	3.39E-01	1.45E-02	23.428	<2e-16	***
LogDvmt	-2.09E-01	1.23E-03	-169.879	<2e-16	***
Hhincttl:LogDvmt	-6.51E-08	8.75E-09	-7.444	9.95E-14	***
LogDen:LogDvmt	-5.10E-03	1.62E-04	-31.602	<2e-16	***
LogSize:LogDvmt	8.57E-02	5.41E-04	158.515	<2e-16	***
Urban:LogDvmt	1.52E-02	1.10E-03	13.821	<2e-16	***
Hhincttl:Urban	2.33E-07	3.45E-08	6.751	1.49E-11	***
LogDen:Urban	-5.03E-02	1.49E-03	-33.661	<2e-16	***
LogSize:Urban	1.66E-02	2.18E-03	7.614	2.71E-14	***

Signif. codes: 0 *** 0.001
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 60: Estimation Results for Linear Model of the Proportion of Household DVMT in SOV Tours <= 20 Miles

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	1.04E+00	4.71E-03	220.281	<2e-16	***
Hhincttl	2.23E-06	5.71E-08	39.053	<2e-16	***
LogDen	1.85E-02	6.19E-04	29.864	<2e-16	***
LogSize	-3.75E-01	3.43E-03	-109.122	<2e-16	***
Urban	3.46E-01	1.39E-02	24.981	<2e-16	***
LogDvmt	-2.24E-01	1.23E-03	-182.199	<2e-16	***
Hhincttl:LogDvmt	-3.85E-07	8.68E-09	-44.314	<2e-16	***
LogDen:LogDvmt	-9.63E-04	1.64E-04	-5.857	4.73E-09	***
LogSize:LogDvmt	8.33E-02	5.37E-04	155.237	<2e-16	***
Urban:LogDvmt	1.64E-02	1.06E-03	15.454	<2e-16	***
Hhincttl:LogDen	-5.61E-08	6.00E-09	-9.346	<2e-16	***
Hhincttl:LogSize	2.15E-07	1.96E-08	10.933	<2e-16	***
Hhincttl:Urban	1.43E-07	3.63E-08	3.953	7.73E-05	***
LogDen:LogSize	-2.77E-03	3.74E-04	-7.405	1.33E-13	***
LogDen:Urban	-5.04E-02	1.43E-03	-35.237	<2e-16	***
LogSize:Urban	1.08E-02	2.29E-03	4.695	2.68E-06	***

Signif. codes: 0 *** 0.001
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:

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

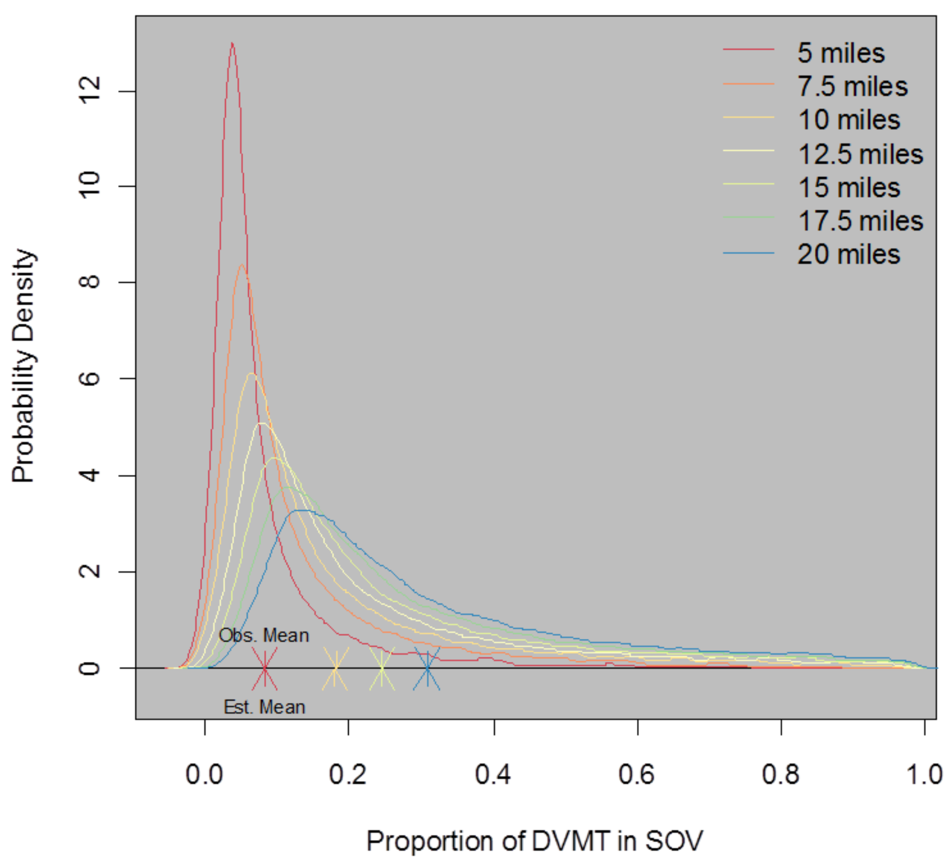
The alpha and beta parameters of the transform were estimated by iterating over sequences of values to find the parameters that produced the best fit. Two statistics were used to assess the degree of fit:

- 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.

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 5 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 37 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 5-, 10-, 15-, and 20-mile thresholds with the mean values from the survey.

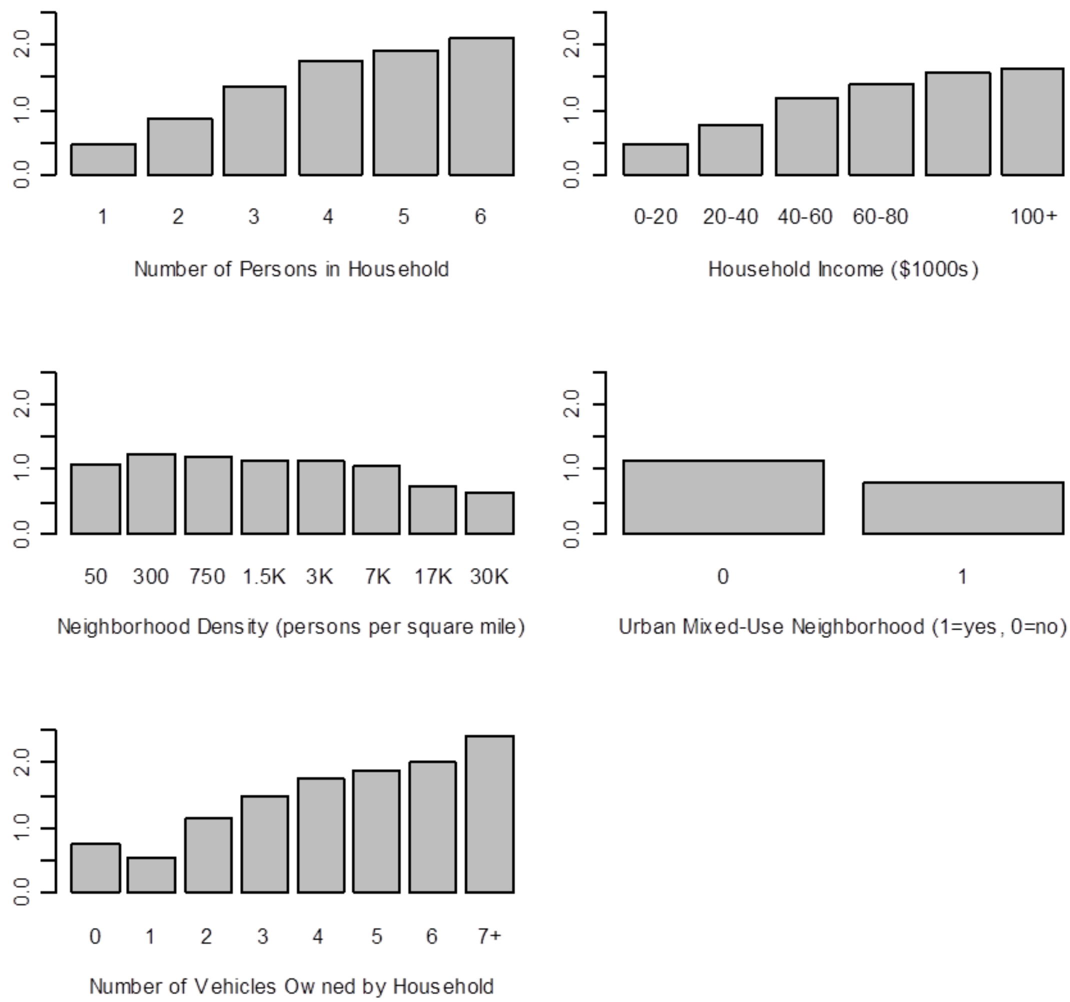
Figure 37: Comparison of Modeled Distributions of SOV Travel Proportions by Tour Mileage Threshold



15.2 Estimating a Non-motorized Vehicle Ownership Model

A non-motorized vehicle ownership model was estimating using NHTS survey data on the number of full-sized bicycles in the household. Figure 38 shows how the mean number of full-sized bicycles owned varies with household and environmental characteristics.

Figure 38: 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 61 shows the model estimation results for the metropolitan household model. Table 62 shows the results for the non-metropolitan household model.

The function written to implement the non-motorized vehicle ownership model allows the user to input a target non-motorized vehicle ownership rate (average ratio of non-motorized 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.

Table 61: Metropolitan Household Non-motorized Vehicle Ownership Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	2.40E-01	3.18E-02	7.521	5.71E-14	***
Census_rMidwest	1.86E-01	2.70E-02	6.901	5.38E-12	***
Census_rSouth	-1.47E-01	2.24E-02	-6.568	5.26E-11	***
Census_rWest	-1.52E-02	2.83E-02	-0.536	0.59179	
Hhsize	1.66E-01	9.66E-03	17.198	<2e-16	***
Hhincttl:Age15to19	3.57E-06	4.88E-07	7.322	2.57E-13	***
Hhincttl:Age30to54	2.49E-06	2.10E-07	11.821	<2e-16	***
Hhincttl:Age55to64	1.72E-06	3.76E-07	4.57	4.92E-06	***
Age15to19:VehPerDrvAgePop	2.17E-01	3.86E-02	5.623	1.91E-08	***
VehPerDrvAgePop:Age20to29	1.64E-01	3.57E-02	4.609	4.07E-06	***
Age30to54:VehPerDrvAgePop	1.99E-01	1.59E-02	12.521	<2e-16	***
Age55to64:VehPerDrvAgePop	2.12E-01	2.78E-02	7.652	2.10E-14	***
VehPerDrvAgePop:Age65Plus	1.48E-01	2.78E-02	5.338	9.55E-08	***
Age20to29:LogDen	-1.40E-02	4.63E-03	-3.034	0.00242	**
Age30to54:LogDen	-1.57E-02	2.84E-03	-5.551	2.90E-08	***
Age55to64:LogDen	-2.64E-02	4.65E-03	-5.687	1.32E-08	***
Age65Plus:LogDen	-2.47E-02	3.63E-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, Adj. R-squared: 0.2252, F-statistic: 282.2 on 16 and 15462 DF, p-value: < 2.2e-16

Table 62: Non-metropolitan Household Non-motorized Vehicle Ownership Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	1.68E-01	2.54E-02	6.619	3.69E-11	***
Census_rMidwest	2.55E-01	1.84E-02	13.893	<2e-16	***
Census_rSouth	-3.94E-01	2.16E-02	-18.229	<2e-16	***
Census_rWest	-2.55E-01	2.50E-02	-10.216	<2e-16	***
Hhsize	1.56E-01	7.00E-03	22.309	<2e-16	***
Hhincttl:Age15to19	3.20E-06	4.72E-07	6.786	1.18E-11	***
Hhincttl:Age30to54	2.91E-06	1.84E-07	15.795	<2e-16	***
Hhincttl:Age55to64	2.13E-06	3.07E-07	6.932	4.22E-12	***
Hhincttl:Age65Plus	1.35E-06	3.24E-07	4.177	2.96E-05	***
Age15to19:VehPerDrvAgePop	1.60E-01	2.84E-02	5.649	1.62E-08	***
VehPerDrvAgePop:Age20to29	8.26E-02	1.36E-02	6.082	1.20E-09	***
Age30to54:VehPerDrvAgePop	1.43E-01	1.06E-02	13.499	<2e-16	***
Age55to64:VehPerDrvAgePop	1.28E-01	1.64E-02	7.781	7.41E-15	***
Age65Plus:VehPerDrvAgePop	1.15E-01	1.71E-02	6.751	1.50E-11	***
Age15to19:LogDen	2.74E-02	5.27E-03	5.206	1.95E-07	***
Age30to54:LogDen	6.48E-03	2.39E-03	2.715	0.00663	**
Age55to64:LogDen	-8.21E-03	3.72E-03	-2.209	0.02717	*
Age65Plus:LogDen	-2.30E-02	3.08E-03	-7.485	7.37E-14	***

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05
Residual standard error: 1.163 on 29502 degrees of freedom (64 observations deleted due to missingness)
Multiple R-squared: 0.2704, Adj. R-squared: 0.27, F-statistic: 643.2 on 17 and 29502 DF, p-value: < 2.2e-16

15.3 Calculating Non-motorized Weight Vehicle DVMT

Non-motorized 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 non-motorized vehicle travel

(an input assumption)

LtVehicleOwnRatio = ratio of non-motorized vehicles to number of driving age persons

(non-motorized vehicle ownership calculated by model)

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

16 CALCULATE HEAVY TRUCK VMT AND FUEL ECONOMY

The following is a description of the model for forecasting freight GHG emissions. It only addresses emissions from heavy trucks. 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. 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.

The forecast of heavy truck VMT is straightforward. Future total statewide income is calculated from the forecasts of statewide population and average per capita 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 needs to be attributed to metropolitan areas to calculate metropolitan congestion. This is done by applying fixed proportions calculated for the base year (2005) using data from state highway vehicle counts, the Federal Highway Cost Allocation Study,[28] and HPMS data. Traffic count data for state highways is used to allocate truck VMT between urbanized and non-urbanized areas. The Federal Highway Cost Allocation Study is used to calculate the average proportion of truck VMT by urban area functional class (Table 63). The amount of the VMT in each urbanized area that is truck VMT is calculated by applying the proportions calculated in Table 63 to the HPMS estimates of VMT by functional class calculated for each urbanized area. The proportions of total state truck VMT in each urbanized area are then calculated from those results.

[28] Table II-6, 1997 Federal Highway Cost Allocation Study Final Report, Chapter II, http://www.fhwa.dot.gov/policy/hcas/final/two.htm

Table 63: Heavy Truck VMT Proportions by Urban 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%

Average fleet fuel economy for heavy trucks is calculated similarly to the way in 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.

17 CALCULATE BUS AND PASSENGER RAIL VMT FOR EACH METROPOLITAN AREA

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 traveled by multiplying the revenue miles by a factor that accounts for non-revenue service travel. A statewide average of 1.12 is used.

Fleet average bus fuel economy and rail energy efficiency are computed in the same fashion as heavy truck fuel economy.

18 ADJUSTING METROPOLITAN AREA FUEL ECONOMY TO ACCOUNT FOR CONGESTION

Household, truck, and bus DVMT in metropolitan areas is allocated to the simplified functional classifications of freeways, arterials, and other roadways. Estimates of congestion are made for freeways and arterials in order to adjust average fleet fuel economy in response to congestion.

Metropolitan household, heavy truck, and bus VMT are summed to compute total road-system VMT by metropolitan area. This is allocated in two ways to freeways, arterials, and other roads in each metropolitan area. For trucks and buses, the allocations are made using fixed proportions by urbanized area. The truck proportions were calculated from the data sources identified in the previous section. The bus proportions are calculated from the Federal Highway Cost Allocation Data identified in the previous section and from data provided by public transit agencies. The auto and light truck proportions are calculated in two steps. In the first step, the combined proportion of VMT on freeways and other arterials is calculated as a fixed proportion for each metropolitan area using the data sources and methods described in the previous section. In the second step, auto and light truck VMT is split between freeways and other arterials using data derived from the 2009

Texas Transportation Institute Urban Mobility Report (based on 2007 data) augmented with VMT proportions calculated from Highway Statistics Table HM-71. Table 64 summarizes the regression model that splits auto and light truck VMT between freeways and other arterials.

Table 64: Freeway and Arterial DVMT Proportions Model

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.07686	0.06621	1.161	0.249	
LnMiRatio.	2.59032	0.17742	14.6	<2e-16	***

Residual standard error: 0.2139 on 88 degrees of freedom

Multiple R-squared: 0.7078,   Adjusted R-squared: 0.7045

After VMT is divided between freeways and arterials, estimates are made of the proportions of VMT experiencing different levels of congestion. Urban Mobility Report categories and data are used to create the models for this. Five categories are used to describe different congestion levels: uncongested, moderately congested, heavily congested, severely congested, and extremely congested. There are reasonably strong relationships between DVMT proportions and system-wide ratios of DVMT to lane-miles. Figure 39 shows the relationship for freeways and Figure 40 shows the relationship for arterials. The portion of DVMT allocated to the moderately congested category is treated as a remainder because the relationship for that category is very weak.

Figure 39: Freeway DVMT Percentages by Congestion Level Vs. Average Daily Traffic Per Lane

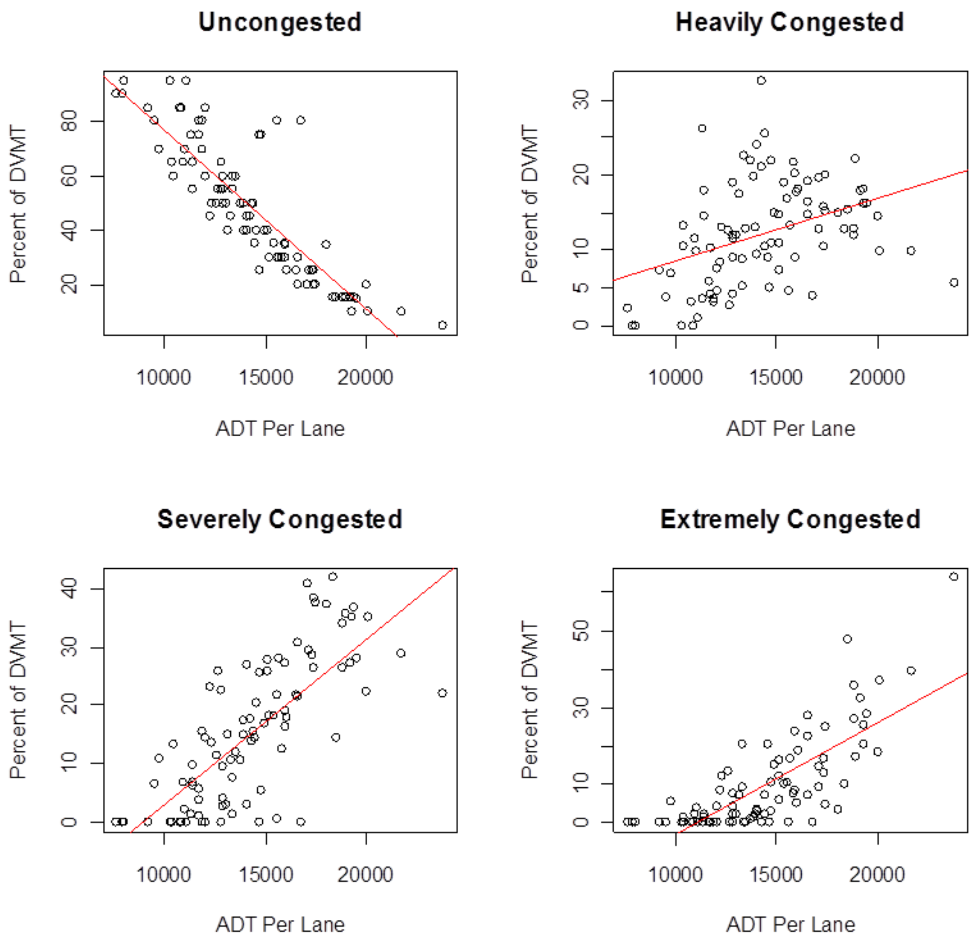
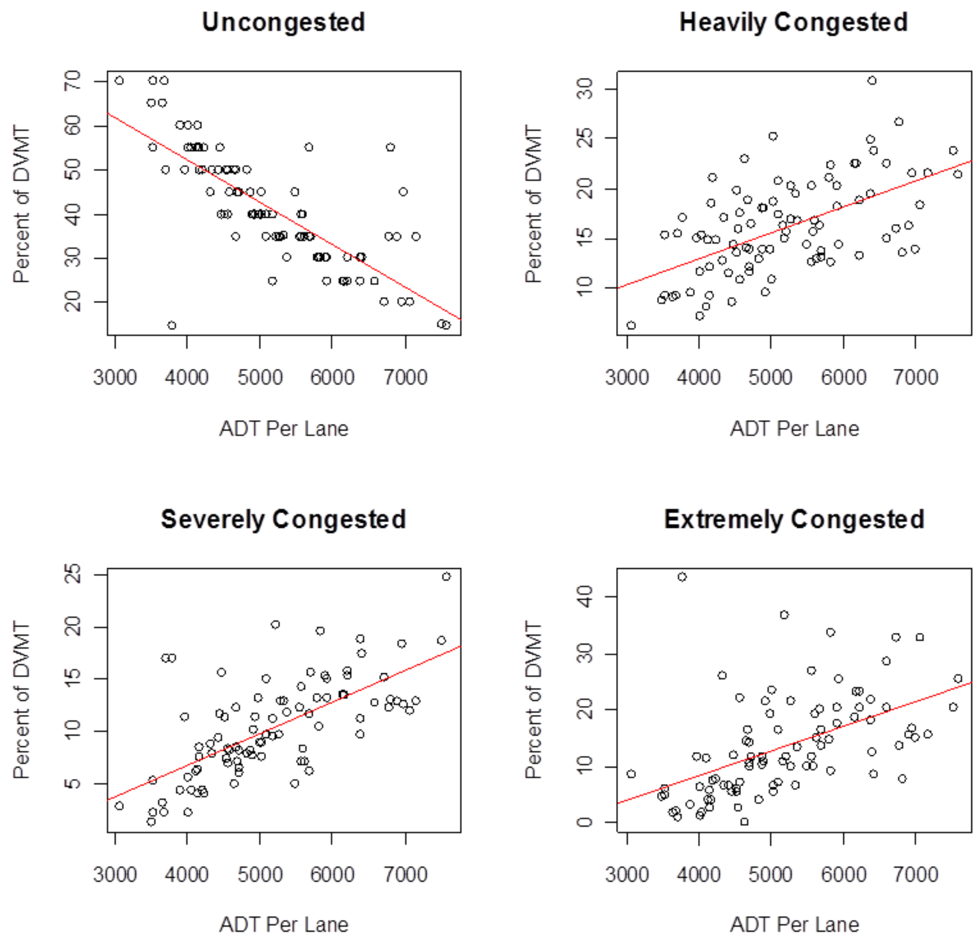


Figure 40: Arterial DVMT Percentages by Congestion Level Vs. Average Daily Traffic Per Lane



The Urban Mobility Report calculates average trip speeds for each congestion level. Two sets of speeds are provided. One set accounts for the effects of recurring congestion on speeds. The other set accounts for the effects of highway incident-related congestion as well as recurring congestion. Figure 41 shows the speed data for freeways for all metropolitan areas included in the study. Figure 42 shows the speed data for arterials. The abscissa shows the percentage of the freeway or arterial DVMT operating at the congestion level. The ordinate shows the corresponding average speeds with and without incidents.

The model uses the mean speeds with and without incidents to compute an overall average speed by road type and congestion level. The approach provides a simple level of sensitivity testing of the potential effects of incident management programs on emissions. An average speed is calculated for each congestion level by interpolating between the incident and non-incident speeds based on an assumed reduction in incidents. For example, an assumed reduction of 0.5 would result in a calculated value that is midway between the incident and non-incident speed levels. Speeds are treated differently for autos, light trucks, and heavy trucks than for buses. For the former, speeds are derived from the congestion models just described for freeways and arterials. Speeds on other roadways are assumed to be 20 MPH and unaffected by congestion. For bus VMT on freeways, speeds are those calculated for freeways as described, but for arterials and other local streets, speeds are based on bus service characteristics derived from transit agency data. The assumed speed for arterial service is one standard deviation above the mean of all bus routes (21 MPH). The assumed speed for other roadway service is one standard deviation below the mean (13 MPH). These values are rounded to 20 MPH and 15 MPH, respectively.

Figure 41: Estimated Freeway Speeds by Congestion Level

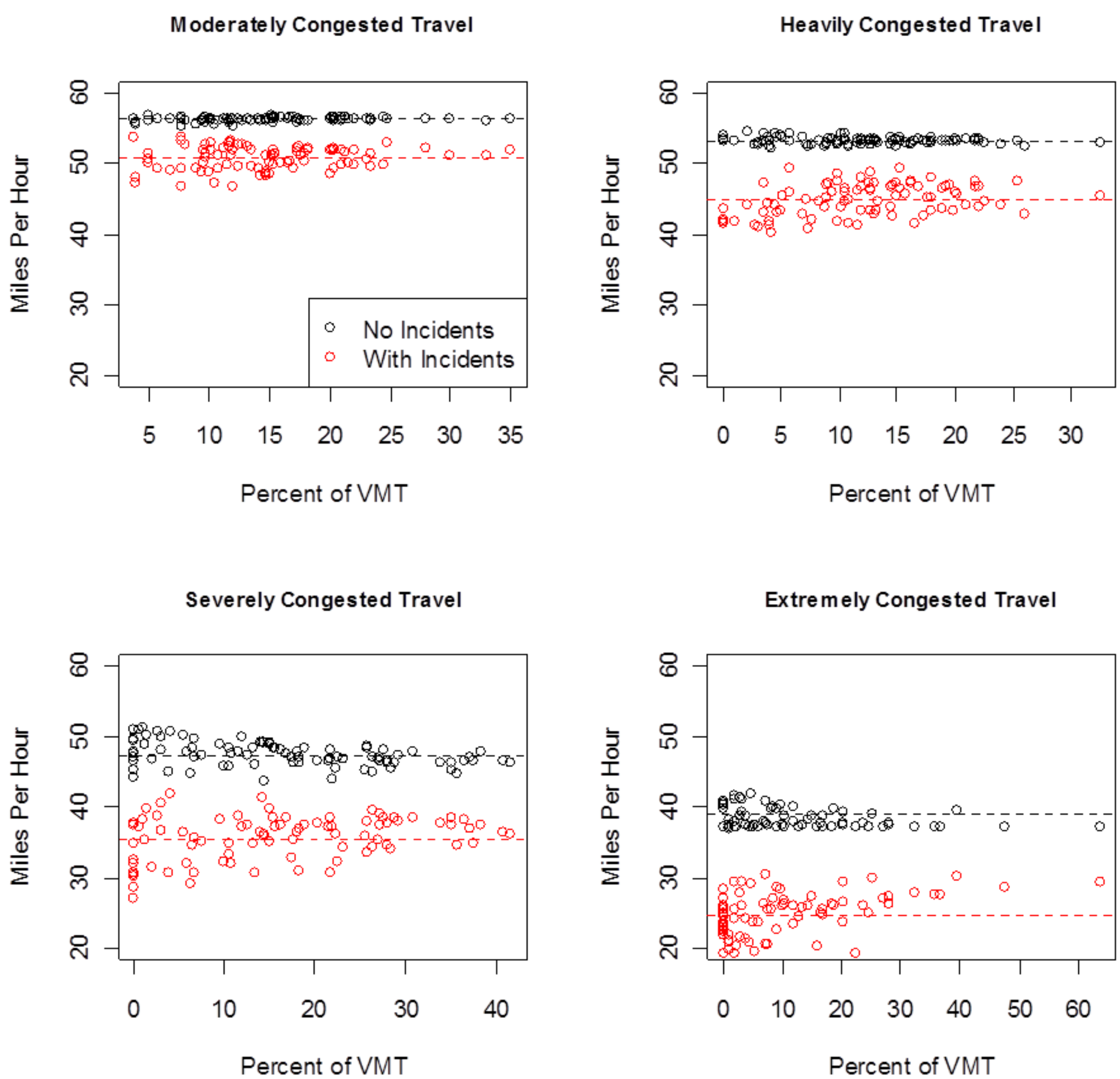
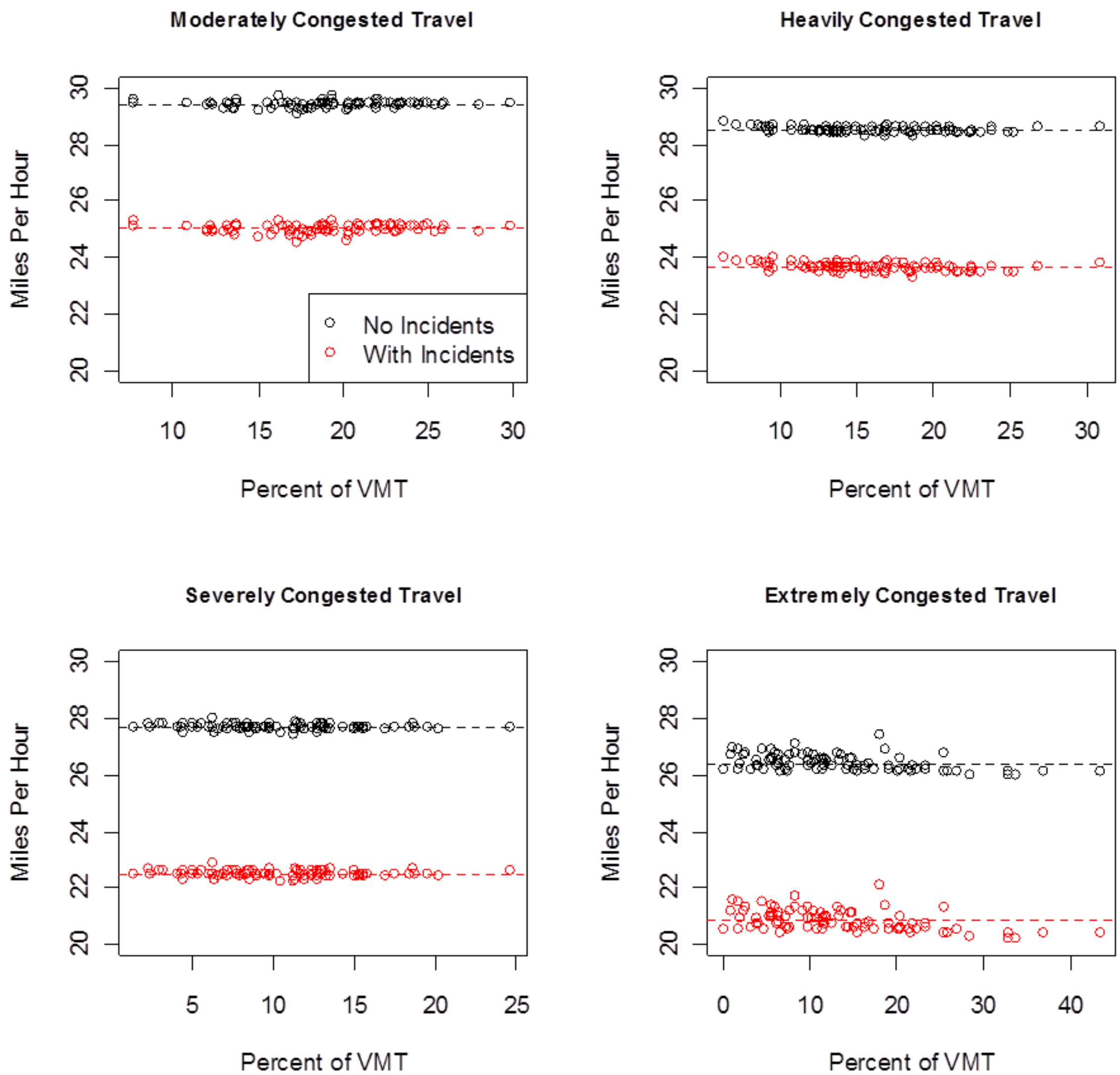


Figure 42: Estimated Arterial Speeds by Congestion Level



Once metropolitan VMT by vehicle type has been allocated to speed bins, fuel economy is calculated using speed and fuel economy curves. Vehicle fuel economy drops off at low speeds and at very high speeds. The relationship between speeds and fuel economy was compiled by the FHWA using the EPA's MOVES model [29] and from the Transportation Energy Data Book[30] Figure 43 compares these sources. All values are indexed to the fuel economy values at 60 MPH to facilitate comparison. Based on this comparison, a decision was made to use the data prepared by Houk for buses and trucks and the data from the Energy Data Book for autos and light trucks.

[29] Jeff Houk, Federal Highway Administration, personal communication. These curves were derived from the MOVES model.

[30] Davis, Diegel, & Boundy, Transportation Energy Databook, 29th Edition, U.S. Department of Energy, Oak Ridge National Laboratory, July 2010, Table 4.29.

Once the overall fuel economy-speed curves were established, normalized curves were developed for each functional classification. Normalization was simply the division of the fuel economy at each speed level by the fuel economy at the assumed freeflow speed for each functional classification (freeway = 60 MPH, arterial = 30 MPH, other = 20 MPH). This normalization is necessary because average fleet fuel economy values already account for the split of travel between "highway" and "city" driving. If fuel economy were adjusted relative to freeway speeds there would be a double counting of the effects of "city" driving on fuel economy. Bus fuel economy normalization on arterials and other roadways is based on the respective average estimated service speeds, 20 MPH and 15 MPH, respectively. Figure 44 shows the normalized curves for freeways. Figure 45 shows the normalized curves for arterials. In Figure 45 the bus value is 1 at 20 MPH rather than 30 MPH. That is because the assumed route speed for buses on arterials is 20 MPH. The model caps bus speeds at 20 MPH on arterials. Since it is assumed that "other roadways" are unaffected by congestion, fuel economy for VMT occurring on these roadways is not adjusted in response to speed.

Figure 43: Comparison of Fuel Economy – Speed Curves from Houk and Energy Data Book

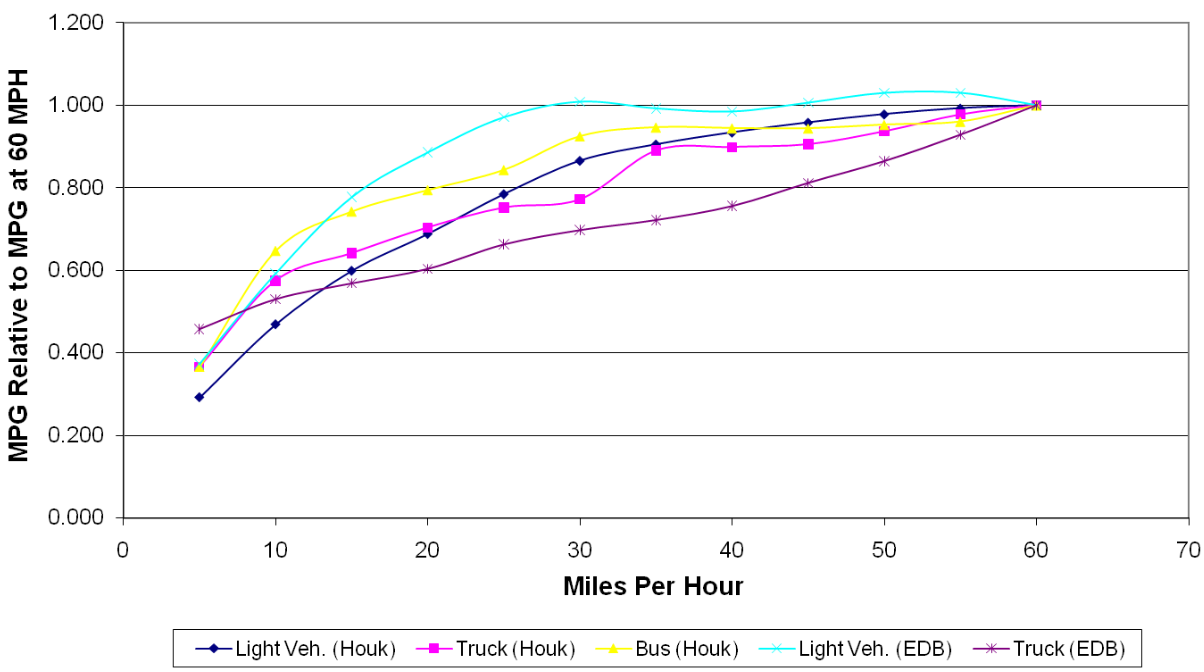


Figure 44: Freeway Speed and Fuel Economy Relationships by Vehicle Type

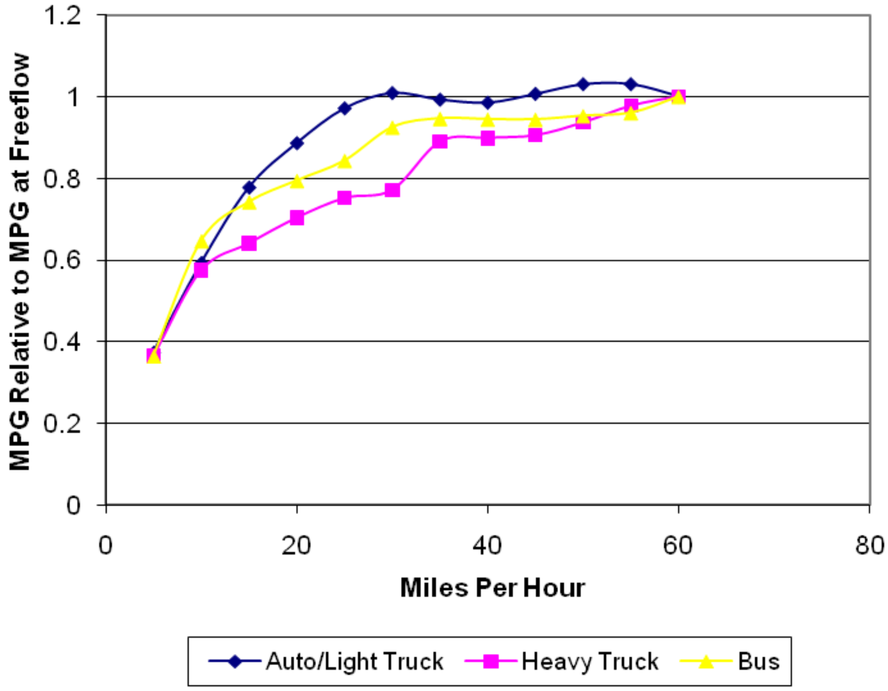
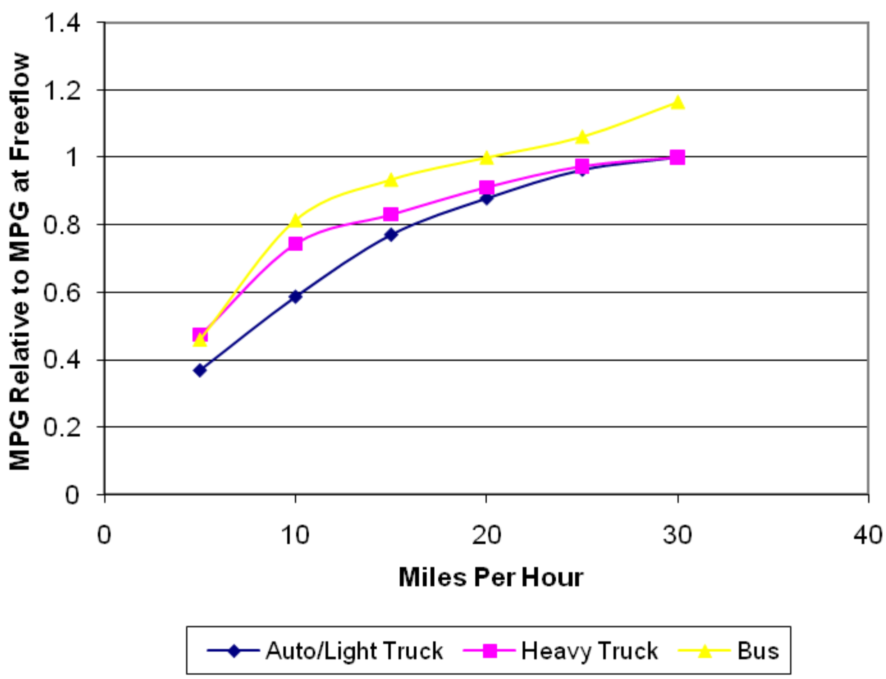


Figure 45: Arterial Speed and Fuel Economy Relationships by Vehicle Type



Energy efficiency is not adjusted for electric vehicles because of the higher efficiency of electric motors over a wider range of speeds. In addition, EVs can use regenerative braking to recover energy when the vehicle slows down.

19 CALCULATE FUEL CONSUMPTION, ELECTRIC POWER CONSUMPTION, AND GREENHOUSE GAS EMISSIONS

At this point in the model, fuel consumption (in gasoline equivalent gallons) by vehicle type can be calculated from the respective estimates of VMT and fuel economy. These estimates are then split into fuel types. The model addresses five fuel types: gasoline, ultra low-sulfur diesel (ULSD), ethanol, biodiesel, and CNG. For each vehicle type, input data specify the fuel proportions by year. These data can be changed for future year scenarios to represent various fuels policies and assumptions.

For light vehicles (automobiles and light trucks), the first step is to allocate fuel consumed between gasoline, CNG, and diesel types. Past, present and future proportions are specified in an input file (see example in Table 65). Different proportions are provided for automobiles and light trucks. Fuel for gasoline engines is then split between gasoline, ethanol, and CNG based on input proportions. Similarly, diesel fuel use is split between ULSD and biodiesel.

A similar process is used to split heavy truck and bus fuel consumption into fuel types. For buses, the splits are specified at the metropolitan area level because there can be substantial differences in the mixes of fuel types used in different metropolitan areas.

Table 65: Example of Light 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

Once fuel consumption is split into the five types (measured in gasoline equivalent gallons), CO_2 equivalents of emissions can be calculated in a straightforward manner. The energy value of the fuel consumed by type is calculated by multiplying by the energy value of a gallon of gasoline. Then the CO_2 equivalent (CO_2e) emissions are calculated by applying the appropriate carbon intensities (grams CO_2e per mega joule) of each fuel type. Values reflect "pump-to-wheels" emission rates, representing just the tailpipe emissions and do not include the "well-to-pump" emissions resulting from the production and transportation of fuels. Table 66 shows the values provided in example implementations of the FHWA tool. The values are derived from the MOVES database (the fuel sub type table provides carbon contents and oxidation factors) and from Emission Facts: Greenhouse Gas Emissions from a Typical Passenger Vehicle[31] to convert to CO_2 equivalents (which includes the global warming potential of other gases emitted by vehicles such as CH4, N2O, and HFCs).

[31] http://www.epa.gov/oms/climate/420f05004.htm#step4

Table 66: Carbon Intensity by Fuel Type (Grams CO_2e Per Mega Joule)

Fuel Type	Carbon Intensity (gm per mega joule)
Ultra-low sulfur diesel (USLD)	77.19
Biodiesel	76.81
Reformulated gasoline (RFG)	75.65
CARBOB (gasoline formulated to be blended with ethanol)	75.65
Ethanol	74.88
Compressed natural gas (CNG)	62.14

It should be noted that the "well-to-pump" emissions for the different fuel types could change over time as technologies for producing the fuels change. For example, the ethanol number assumes present technology, which is dominated by production of ethanol derived from corn. As cellulosic ethanol production increases, the ethanol average value will fall. However, the "pump-to-wheels" emissions would remain constant over time.

Electric power consumption for EVs is converted into CO_2 equivalents using a rate of emissions per kilowatt hour of electric power consumed. Rates are computed by county based on the distribution of customers among power providers in the county and the different emission rates of the power providers. The emissions rates are end-user values rather than source values so they include power transmission loss effects. They therefore represent the full CO_2 equivalent emissions for EVs.

All of the light vehicle calculations of fuels and emissions are done at the disaggregate level of county, income group, and development type. This allows emissions to be reported at this level of disaggregation as well. The public transportation emissions are calculated at the metropolitan level. Heavy truck emissions are also calculated at the metropolitan level using the VMT splits described earlier. Non-metropolitan heavy truck emissions are calculated in one category.

20 REFERENCES

Bento, A. M., M. L. Cropper, A. M. Mobarak, and K. Vinha. "The Effects of Urban Spatial Structure on Travel Demand in the United States." *Review of Economics and Statistics*, Vol. 87, No. 3, pp. 466–478. 2005

Cambridge Systematics, Inc. *Moving Cooler: An Analysis of Transportation Strategies for Reducing Greenhouse Gas Emissions*. Urban Land Institute, Washington, D.C., 2009.

Cervero, Robert. "Are Induced-Travel Studies Inducing Bad Investments?" *Access*, No. 22, Spring 2003, pp. 22-27.

Cervero, Robert. "Road Expansion, Urban Growth, and Induced Travel: A Path Analysis." Department of City and Regional Planning, Institute of Urban and Regional Development, University of CA, Berkeley, July 2001.

Cervero, Robert, et al. "City CarShare: Longer-Term Travel Demand and Car Ownership Impacts." *Transportation Research Record: Journal of the Transportation Research Board*, No. 1992, Transportation Research Board of the National Academies, Washington, D.C., 2007, pp. 70-80.

Dong, Hongwei, John D. Hunt, Tara Weidner. "Linking Fuel Prices, Transportation, Land Use and Economic Activity: A Review of Empirical Findings." Report produced for the Oregon Department of Transportation-draft. January 2010.

Harvey, Greig, Elizabeth Deakin. "The STEP Analysis Package: Description and Application Examples," Appendix B, in *Technical Methods for Analyzing Pricing Measures to Reduce Transportation Emissions*, USEPA,

Report #231R98006 as cited in Victoria Transport Policy Institute, "Pay-As-You-Drive Vehicle Insurance: Converting Vehicle Insurance Premiums Into Use-Based Charges." *TDM Encyclopedia*, 1998. http://www.vtpi.org/tdm/tdm79.htm.

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

Kuhnimhof, Tobias, Christoph Gringmuth, "Multiday Multiagent Model of Travel Behavior with Activity Scheduling," *Transportation Research Record: Journal of the Transportation Research Board*, No. 2134, Transportation Research Board of the National Academies, Washington, D.C., 2009, pp. 178-185.

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.

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.

Miller, David R., Ken Hodges. "A Population Density Approach to Incorporating an Urban-Rural Dimension into Small Area Lifestyle Clusters." Claritas Inc. Presented at the Annual Meeting of the Population Association of American, May 1994. http://knowledge.fhwa.dot.gov/cops/hcx.nsf/All+Documents/406F76EEA4583F9685257417006E5E98/$FILE/ClaritasScan001.pdf

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.

Pickrell, Don, 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. http://nhts.ornl.gov/1995/Doc/Envecon.pdf.

Shrank, David, Tim Lomax. "2009 Annual Urban Mobility Report." Texas Transportation Institute, the Texas A&M University System. July 2009. http://mobility.tamu.edu.

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

Small, Kenneth A., Kurt Van Dender. "If Cars Were More Efficient, Would We Use Less Fuel?" *Access*, Number 31, Fall 2007.

Strathman, James G., Kenneth J. Dueker, Thomas Sanchez, Jihong Zhang, Anne-Elizabeth Riis. "Analysis of Induced Travel in the 1995 NPTS." Center for Urban Studies, College of Urban and Public Affairs, Portland State University, Portland, OR, June 2000.

Transportation Research Board. "Driving and the Built Environment: Effects of Compact Development on Motorized Travel, Energy Use, and CO2 Emissions." Special Report 298. September 2009.

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.

U.S. Department of Transportation, Federal Highway Administration. "Table HM-71, Urbanized Areas – 2007 Miles and Daily Vehicle - Miles Traveled." Highway Statistic Series, Highway Statistics 2007. October 2008. http://www.fhwa.dot.gov/policyinformation/statistics/2007/hm71.cfm.

U.S. Department of Transportation, Federal Highway Administration. *2001 National Household Travel Survey User's Guide.* January 2004 (Version 3). http://nhts.ornl.gov/2001/usersguide/UsersGuide.pdf

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.

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.

Victoria Transportation Policy Institute, "Carsharing," *TDM Encyclopedia,* http://www.vtpi.org/tdm/tdm7.htm

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.

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

21 ABBREVIATIONS USED IN THIS REPORT

ADT	Average daily traffic
CARB	California Air Resources Board
CARBOB	Gasoline formulated to be blended with ethanol
CBO	U.S. Congressional Budget Office

CES	Consumer expenditure survey
CNG	Compressed natural gas
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
DEQ	Oregon Department of Environmental Quality
DMV	Department of Motor Vehicles
DVMT	Daily vehicle miles traveled
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
HPMS	Highway Performance Monitoring System
HTHUR	Census tract level urban/rural continuum code used to classify area type in metropolitan areas.
IPF	Iterative proportional fitting
MOVES	Motor Vehicle Emission Simulator model
MPG	Miles per gallon
MPH	Miles per hour
MPKWH	Miles per kilowatt hour
NHTS	National Household Travel Survey
NPTS	National Personal Travel Survey
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
R	Open source programming language
RFG	Reformulated gasoline
SOV	Single-occupant vehicle
TDM	Transportation demand management
TRB	Transportation Research Board
UGB	Urban growth boundary
ULSD	Ultra low sulfur diesel fuel
UMS	Urban Mobility Study
VMT	Vehicle miles traveled