ABSTRACT

Title of Thesis:	A MODEL SYSTEM TO EVALUATE THE IMPACTS OF VEHICLE-RELATED TAXATION POLICIES ON HOUSEHOLD GREENHOUSE GAS EMISSIONS.
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This thesis proposes a model system to forecast household-level greenhouse gas emissions (GHGEs) from private transportation and to evaluate effects of car-related taxation schemes on vehicle emissions. The system contains four sub-models which specifically capture households' vehicle type and vintage, quantity, usage, and greenhouse gas emissions rates for different vehicle types. An integrated discrete-continuous vehicle ownership model is successfully implemented, while MOVES2014 (Motor Vehicle Emission Simulator 2014) is utilized. The model system has been applied to the Washington D.C. Metropolitan Area. The 2009 National Household Travel Survey (NHTS) with supplementary data from the *Consumer Reports*, the *American Fact Finder* and the 2009 State Motor Vehicle Registrations (SMVR) are used for estimations and predictions. Three tax schemes, vehicle ownership tax, purchase tax and fuel tax, have been proposed and their impacts on vehicle GHGEs reduction are predicted. The proposed model system can be extended to other regions, counties, states and nations.

A MODEL SYSTEM TO EVALUATE THE IMPACTS OF VEHICLE-RELATED TAXATION POLICIES ON HOUSEHOLD GREENHOUSE GAS EMISSIONS

By

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Thesis submitted to the Faculty of the Graduate School of the
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Dedication

This paper is dedicated to my parents, who have always been supportive and encouraged me to pursue my dream.

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Chapter 1: Introduction

1.1 Background and Overview

Increases in mobility demand and motorization rates have caused unsustainable levels of congestion and pollution worldwide. Specifically, energy consumption and pollutant emissions from the transportation sector have increased significantly in recent decades. In the United States, according to the United Nations Framework Convention on Climate Change (UNFCCC) annual report, 27% of total Greenhouse Gas Emissions (GHGEs) were from the transportation sector in 2011. Within the transportation sector, light-duty vehicles were the largest pollutant sources, accounting for 61% of the total GHGEs (*1*). Although mobile sources contribute large percentages of pollutants, technology is not yet available to measure and tax emissions from each vehicle (*2*). Given the important role of private transportation, it is necessary to apply effective, innovative and quantitative methodologies to support public authority decision making and to analyze the impacts of taxation policies on the reduction of GHGEs (*3*).

In regional travel modeling and simulation, the combination of the number of vehicles owned by a household, vehicle type and vintage, and the usage (measured in vehicle-miles-traveled (VMT)) of vehicles is an important determinant of households' vehicle GHGEs, fuel consumption, and pollutant emissions (*4*). The state-of-the-art in calculating GHGEs from vehicle usage (VMT) employs either the standard values of conversion that consider lifecycle emissions from the Environmental Protection Agency (EPA) or the emission rates per miles from the California Air Resources

Board (CARB) (*2, 5, 6, 7*). Another method to estimate vehicle GHGEs is to combine demand models and emission simulators for emissions forecasting such as the EPA's MOBILE6, the EPA's recently released MOVES model, and the EMFAC model in California (*4*). Because the above approaches cannot dynamically predict GHGEs, Vyas et. al were the first to integrate a household vehicle ownership model with a larger activity-based model micro-simulator system – SimAGENT (the Simulator of Activities, Greenhouse Gas Emissions, Energy, Networks, and Travel) – which is able to dynamically estimate vehicle GHGEs for the households (*4*).

Car ownership models are also applied to study problems resulting from traffic congestion, excessive fuel consumption, high pollutant emission rates and energy demand (*8, 9*). Therefore, both public agencies and private organizations are interested in employing car ownership models for policy analysis (*3*). For instance, the U.S. Department of Energy, the U.S. Department of Transportation, auto industries, and the World Bank all supported studies on car ownership models and used their results for policy analysis (*10*).

To estimate GHGEs, a vehicle ownership model system can be adopted to examine the life cycle CO_2 emissions from automobile transport and the tax revenues of different taxation policies (*11*). Hayashi et al. (*11*) determined the effects of varying the weights of the tax components according to car type and vintage mix and car users' driving patterns and behaviors in Japan. Additionally, national governments use vehicle ownership models to forecast tax revenues and the regulatory impact of different taxation policies (*11, 12, 13*). To summarize, various taxation policies to reduce GHGEs have been considered in recent studies such as vehicle purchase tax, vehicle ownership tax, tax on vehicle driving distance, emission tax, emission rates tax, fuel or gas tax, tax on vehicle age and tax on engine size (*5*, *11*). For private vehicles, a tax to reduce GHGEs can encourage drivers to (*2*): (a) buy a newer or cleaner car, (b) buy a smaller and more fuel efficient car, (c) fix their broken pollution control equipment, (d) use cleaner gasoline, (e) drive less, (f) drive less aggressively and (g) avoid cold start-ups. Multiple researchers have found that fuel or gas taxes are the most effective for GHG emission reduction among all vehicle-related taxes (*5*, *6*, *11*). In the long term, the energy consumption and GHGEs of private vehicles would be affected by gas price dynamics, tax incentives, feebates and purchase prices along with new technologies, government-industry partnerships, range and recharging times (*7*).

1.2 Research Objectives

This thesis proposes a general model system to forecast household-level vehicle GHGEs and to evaluate the effects of car-related taxation schemes on GHGEs. To obtain household-level GHGEs, an integrated vehicle ownership model is used in the system to capture vehicle type and vintage, quantity and usage. MOVES2014, authorized by the EPA, is adopted to estimate GHGEs rates for different types of vehicles. The effects from purchase tax, ownership tax and fuel tax on the reduction of household-level vehicle GHGEs have been predicted and compared.

The remainder of the thesis is organized as follows. Chapter 2 presents literature reviews on empirical integrated vehicle ownership models, and methods to estimate GHGEs. Chapter 3 introduces an integrated model system, which includes the following four sub-models: (a) vehicle type sub-model, (b) vehicle quantity sub-model, (c) vehicle usage regression model and (d) vehicle emission rates estimation. The proposed model system combines an integrated discrete-continuous vehicle ownership model with MOVES2014 to estimate household-level vehicle GHGEs. The model system is applied to 1289 households in the Washington D.C. Metropolitan Area. Chapter 4 describes all data sources used in this research. In Chapter 5, we present the estimation results of the integrated vehicle ownership model, the estimated emission rates on all components of the GHG for different vehicle types and vintage, and the comparison of vehicle GHGEs among households with one, two and three vehicles. In Chapter 6, three taxation plans are proposed to reduce household-level GHGEs. A comparison of the effects of purchase taxes, ownership taxes, and usage taxes is illustrated in this chapter to provide a reference for policy makers. Finally, Chapter 7 presents the summary and avenues for future research.

Chapter 2: Literature Review

2.1 Vehicle Ownership Models

Disaggregate discrete choice models in the form of multinomial or ordered logit have been proposed to forecast household vehicle holding. We cite here a handful of models for different countries around the world: the United Kingdom (UK) (*14*), the Netherlands (*15, 16*), Norway (*17*), Australia (*18*) and the United States (*19, 20*).

Integrated discrete-continuous models have been investigated in the field of marketing since the 1980's. Chintagunta (*21*) summarized the earliest generation of research on household purchase behaviors. Based on his study, discrete choice models were employed to estimate household purchase quantity and brand choice while continuous models were used to estimate purchase time (*22, 23*). Due to the same discrete-continuous nature, integrated modeling frameworks were quickly introduced into the field of transportation, especially for developing activity models and vehicle ownership models. More specifically for vehicle ownership models, the joint decisions of owning one or multiple cars and driving a certain number of miles has been modeled using discrete-continuous models. The earliest generation of discrete-continuous models was derived from the conditional indirect utility function, based on microeconomic theory (*18, 19, 24, 25, 26, 27*).

In 1984, Dubin, McFadden and Hannemann were the first (*28, 29*) to develop an integrated discrete-continuous model to estimate vehicle quantity and car usage. They assumed that households chose the combination of car quantity and vehicle miles traveled with the highest utility.

In 1986, Train (*24*) proposed an integrated discrete-continuous model which used multinomial logit models to estimate vehicle quantity and type and regressions to estimate vehicle usage. Because driving cost is an endogenous variable for vehicle usage regressions, instrumental variables methods were used to avoid problems with endogeneity.

In 2005, Bhat developed multiple discrete-continuous extreme value (MDCEV) models that could be used to jointly estimate households' vehicle type, quantity and VMT (*30*). This model was applied to analyze the impact of demographics, built environment attributes, vehicle characteristics and gasoline prices on household vehicle holding and usage (*31*, *32*). The advantages of the MDCEV model are that: (a) the modeling framework is consistent with random utility theory, (b) the introduction of multiplicative log-extreme value error term into the utility function yields a closed-form expression for probabilities of consuming certain alternatives, (c) it captures trade-offs among the usage of different types of vehicles, and (d) it accommodates a large number of vehicle classifications. Compared to classical discrete-continuous models, the MDCEV approach presents two limitations (Spissu et al. (*33*)). First, the MDCEV model provides a restricted framework that combines the discrete choice and continuous choice with a single stochastic utility function, which can be relaxed to a more flexible form in classical models. Second, an exogenous budget for household total vehicle usage should be considered for the MDCEV model while no such restriction is required for classical models.

In 2006, Bhat and Sen (*31*) applied the MDCEV model to estimate household vehicle quantity and usage of multiple vehicle types for San Francisco Bay Area. The study indicated significant influences on vehicle type, quantity and usage decisions by households' demographics, residential locations and vehicle characteristics. The estimation results from the model could be further investigated in land use decisions, policy analysis, traffic congestion reduction, and air emissions reduction for the San Francisco Bay Area.

In 2009, Bhat et al. (*32*) combined the MDCEV model with a sequential nested model structure which estimated vehicle type and usage on the upper level and estimated vehicle make and model on the lower level.

In 2008, the combined choices of vehicle holding and usage were also studied by Fang (*34*) who proposed a Bayesian Multivariate Ordered Probit and Tobit model (BMOPT). In this model system, an ordered probit model determined households' decisions on vehicle quantity corresponding to two categories (cars and trucks). The multivariate Tobit model was applied to estimate the household decisions on VMT. Overall, the model was well suited for predicting the changes in the number of vehicles and miles traveled for each vehicle type (*34*).

In 2013, Liu. et al. (*3*) developed an integrated discrete-continuous model framework to estimate household vehicle type, quantity and usage. Specifically, a multinomial logit model was used to estimate vehicle type and vintage decisions, a multinomial probit model was employed to estimate household vehicle quantity and a linear regression model was used to estimate household total vehicle usage. The discrete and continuous parts are combined by an unrestricted full variance-covariance matrix of the unobserved factors. Bootstrapping method was applied to improve the estimation on data extracted from the 2009 U.S. National Household Travel Survey (NHTS).

Bhat et al. (*35*) proposed a joint model of household auto ownership and residential location choice to accommodate immigration status and self-selection effects. The two nominal variables considered in the model are residential location and household auto ownership. In addition to demographic and immigrant status variables, the residential location dummy variables that form the observed dependent variables for the residential location choice model appear as the explanatory variables for the auto ownership choice model. In order to avoid high-dimensional integration and expensive computational problems, the model employed the maximum approximated composite marginal likelihood (MACML) approach. In this approach, the likelihood function involves only the computation of univariate and bivariate cumulative distribution functions. The results of model estimation from the use of the San Francisco Bay Area subsample of the 2009 NHTS showed that immigration and length of stay are significant explanatory variables in both the choice of residential location and auto ownership, with immigrants displaying assimilation effects. In addition, their research suggested that immigration variables and self-selection effects should be accounted for in transportation forecasting models for policy decisions.

By using the same MACML approach, Paleti et al. (*36*) offered an econometric model system that simultaneously considered six dimensions of activity-travel choices. The six choice decisions included residential location, work location, auto ownership, commuting distance, commute mode, and the number of stops on commute tours. The model system had been applied to estimate households' choices from a data set extracted from the 2009 NHTS.

Table 2-1 below summarizes the empirical integrated discrete-continuous model frameworks and their corresponding applications related to household vehicle ownership.

TABLE 2 - 1 Summary of Empirical Integrated Discrete-Continuous Models

Authors (Year)	Data (Year)	Sample Size	Choice	Model
Berkovec et al. (1985)	U.S. (1978)	1048 HHs	Vehicle quantity (0, 1, 2, 3), Vehicle type	Nested Logit
Train (1986)	U.S. (1978)	1095 HHs	Vehicle quantity (0, 1, 2, 3), class/vintage, usage	MNL and Regression
Golob et al. (1997)	California (1993)	4747 HHs	Vehicle use by type of vehicle	Structural equation
Bhat and Purugurta (1998)	U.S. (1991, 1990, 1991), Dutch (1987)	3665,3500, 1822,1807 HHs	Vehicle quantity (0, 1, 2, 3, 4)	MNL and Ordered logit
Bhat and Sen (2006)	San Francisco (2000)	3500 HHs	Vehicle type holding and usage	MDCEV
Liu et.al. (2013)	D.C. Metropolitan Area (2009)	1420 HHs	Vehicle quantity (0, 1, 2, 3, 4), type and usage	MNP, MNL and regression
Bhat et al. (2013)	San Francisco (2009)	3335 HHs	Residential location and vehicle ownership	MACML
Paleti et al. (2013)	San Francisco (2009)	1480 employed individuals	Residential location, work location, vehicle ownership, commute mode, commuting distance, num. of stops on commute tours	MACML

**note: "HHs" represents households, "MNL" represents multinomial logit model, "MNP" represents multinomial probit model.*

2.2 Methods to Estimate Vehicle GHGEs

In recent years, several emission estimation models have been proposed – for instance, the California's EMFAC7F, the EPA's MOBILE5a (Vehicle Emission

Modeling software), and the EPA's MOVES (*37*). According to EPA (*38*), two methods can be used to calculate GHGEs: (1) from vehicle GHGEs rates and (2) from vehicle fuel consumption. The first approach became more popular because of the development of MOVES model which estimates GHGEs rates for different vehicle types efficiently. The second approach is more traditional and estimates GHGEs by determining the CO_2 production rate from gasoline and gasoline consumption (*38*). The EPA (*38*) stated that the key steps for calculating GHGEs are:

(a) Determining the CO_2 produced per gallon of gasoline

(b) Estimating the fuel economy (miles per gallon, mpg) of passenger cars and light-duty trucks

(c) Determining the annual VMT

(d) Determining the components of GHG, including CO_2, methane (CH_4), nitrous oxide (N_2O), and hydro-fluorocarbons (HFCs)

(e) Estimating the relative percentages of passenger cars and light-duty trucks

(f) Calculating the annual GHGEs.

Previous literature provides multiple methods to estimate GHGEs at the project-level and county-level. Akcelik and Besley (*39*) described a method to model operating cost, fuel consumption and emissions (CO_2, CO, HC, NOx) in the aaSIDRA intersection analysis and aaMOTION trip simulation software. Their models generated highly accurate emissions because of no simplification of traffic information such as average speed, average running speed and number of stops. However, to guarantee accuracy, the model was limited to intersections and short length roadways. Papson et al. (*40*) analyzed vehicle emissions at congested and uncongested signalized intersections under three scenarios using MOVES at a project-level. The authors calculated emissions with a time-in-mode methodology that combined emission factors (EFs) for each activity mode (i.e., acceleration, deceleration, cruise, idle) with the total time spent in that mode. Their study found that cruising and acceleration produced more than 80% of the total emissions while idling accounted for less than 18% of emissions under all scenarios. Senna et al. (*41*) combined the microscopic traffic simulation model VISSIM with the emission model MOVES to estimate emissions of a 10-mile urban limited-access highway in Orlando, FL. Instead of using MOVES default databases, which are based on sources such as EPA research studies, Census Bureau Vehicle Surveys and Federal Highway Administration (FHWA) travel data, three types of output data were generated from VISSIM runs to correspond with vehicle characterization inputs for MOVES. Their results demonstrated that accurate vehicle emissions could be obtained on a second-by-second based estimation. Specifically, they found that the emission rates were highly sensitive to stop-and-go traffic and the associated driving cycles of acceleration, deceleration and idling.

Many researchers also focus on vehicle emissions at the county-level. For instance, Bai et al. (*42*) estimated the vehicle GHGEs of the county of Los Angeles in California using MOVES and EMFAC models. The framework under which MOVES is applied consists of four major functions (*43*): an activity generator, a source bin distribution generator, an operating mode distribution generator, and an emission calculator. The author stated that, compared to EMFAC model, MOVES is a superior analytical tool for three reasons (*42*). First, MOVES uses a combination of vehicle specific power (VSP) and speed bins rather than speed correction factors to quantify running exhaust emissions. Second, it uses vehicle operating time rather than vehicle miles traveled as the unit of measure for various vehicle activities and emissions. Third, it uses a relational database to manipulate data and enable multi-scale emissions analyses from country-level applications down to link-level applications.

Kota et al. (*44*) evaluated on-road vehicle CO and NOx emission inventories for an area in southeast Texas near Houston using urban-scale source-oriented air quality models –MOVES and MOBILE6.2. Their estimation results suggested that NOx concentrations and surface CO concentrations due to vehicle exhaust were significantly over-estimated using either MOBILE6.2 or MOVES. Vallamsundar and Lin (*45*) made a comparison of GHG and Criteria Pollutant Emissions between MOVES and other macroscopic emission models such as MOBILE6.2 and EMFAC. Their study concluded that in terms of emission estimates, MOBILE6.2 underestimated both NOx and CO_2 compared to MOVES. In addition, methods to estimate CO_2 by the two emission models are different - modal based estimation of CO_2 from total energy consumption in MOVES compared to simplified fuel economy rates in MOBILE. By comparing wintertime CO to NOx ratios of on-road emission inventories using MOVES and MOBILE, Wallace et al. (*46*) found that MOVES significantly overestimated NOx and PM2.5 emissions compared to MOBILE6.2. Besides, hydrocarbon and CO emissions as modelled by MOVES were dominated by engine starting process while NOx emissions were split evenly between engine starting and running processes.

TABLE 2 - 2 Summary of Methods to Estimate Vehicle Emissions

Authors (Year)	Method / Model	Type	Location	Results
Akcelik and Besley (2003)	aaSIDRA intersection analysis, aaMOTION trip simulation software	Inventory	limited to intersections and short roadways	accurate emissions because of no simplification of traffic information
Papson et al. (2012)	MOVES	Inventory	congested and uncongested signalized intersections	cruising and acceleration produced more than 80% of the total emissions while idling accounted for less than 18% of emissions
Senna et al. (2013)	combined VISSIM with the emission model MOVES	Emission rates and Inventory	a 10-mile urban limited-access highway in Orlando, FL	accurate emissions could be obtained on a second-by-second based estimation, emission rates were sensitive to stop-and-go traffic and the associated driving cycles of acceleration, deceleration and idling
Bai et al. (2008)	MOVES and EMFAC models	Emission rates and Inventory	the county of Los Angeles in California	MOVES is superior: (1) combines VSP and speed bins; (2) uses vehicle operating time; (3) apply to multi-scale emissions analyses
Kota et al. (2014)	MOVES and MOBILE6.2 models	Inventory	an area in southeast Texas near Houston	They over-estimated CO and NOx due to vehicle exhaust
Vallamsundar and Lin (2011)	MOVES, MOBILE6.2 and EMFAC models	Inventory	-	MOBILE6.2 underestimated both NOx and CO2 compared to MOVES; estimation of CO2 from total energy consumption in MOVES compared to simplified fuel economy rates in MOBILE
Wallace et al. (2012)	MOVES and MOBILE6.2 models	Inventory	-	MOVES significantly overestimated NOx and PM2.5 emissions compared to MOBILE6.2

2.3 Estimation of GHGEs by Vehicle Ownership Models

Vehicle ownership models predict household vehicle quantity, type and vintage and usage which are necessary determinants of vehicle fuel consumption, GHGEs, and other emissions. Thus, the combination of vehicle ownership models and GHG emission estimations has become a topic of interest in recent years. On the policy side, vehicle ownership models are sensitive to testing the changes of vehicle quantity and usage in response to changes in fuel price, household social-demographic and related policies (*47*).

Dargay and Gately (*9*) applied a car ownership model to forecast the growth of household vehicle quantity in 2015 for the Organization for Economic Co-operation and Development (OECD) countries and estimated the growth of energy demand and emissions. They forecasted a range of fuel consumption and CO_2 emissions by estimating trends in car ownership, income, population, vehicle usage, fuel efficiency and fuel price.

In 2001, Hayashi et al. (*11*) proposed a model system that specifically determined the effects of different components of taxation policies in the stages of (a) car purchase, (b) car ownership, and (c) car usage. The model system was applied to analyze the impact of the 1989 tax reform policy in Japan and to forecast future GHGEs reduction under different taxation schemes.

Fullerton et al. (*5*) developed a joint discrete-continuous model from the one by Dubin and McFadden (1984). Their model simultaneously estimated vehicle ownership and driving distance on an aggregated data set extracted from the 47 prefectures in Japan. Two series of travel-related taxation policies on both vehicle characteristics and driving distance were tested. In terms of vehicle driving distance, four taxes were investigated: (a) a tax per unit of local emission; (b) a tax per unit of CO_2 emission; (c) a tax per liter of gasoline; and (d) a tax per kilometer driven. In terms of car characteristics, the authors were interested in three taxes: (a) a tax on engine size; (b) a tax on the emission rate; and (c) a tax on vehicle age. Due to the nature of discrete-continuous models, both choice of vehicle ownership and choice of driving distance were affected by a tax on driving distance or a tax on vehicle characteristics. The results from their research indicated that (a) changes in income influenced both vehicle ownership and driving distance decisions and (b) the impact on emission reduction from taxes on fuel cost was more significant than taxes on vehicle characteristics.

Meanwhile, Fullerton and Gan (*6*) used an integrated discrete and continuous model to estimate vehicle quantity, type and vehicle miles traveled (VMT) simultaneously. Data from the California Air Resources Board (CARB) on 672 vehicles of various types and ages were used to estimate miles per gallon (MPG) and emissions per mile (EPM) as functions of vehicle type, age, and number of cylinders. Estimated parameters were used to compute the MPG and EPM for each vehicle in the Consumer Expenditure Survey (CEX). Their model system employed 9027 households' information from the 1996-2001 CEX, including demographic characteristics, total expenditures, gas expenditures, vehicle type, make and model year. Fuel prices for each year and region were taken from the ACCRA cost-of-living indices. The results from their research indicated that the gas tax was the most cost-effective among all tested taxes. Besides, if the ideal emission tax was not feasible, a cost-effective policy might combine this emission tax to change vehicle ownership and a gas tax to change VMT.

Feng et al. (*2*) developed a nested logit structure to model choices among different vehicle bundles. The authors considered the miles traveled and the age of each vehicle as continuous choices. To model the effect of prices on the choice of vehicle age, they established a choice of "concept vehicle" that is separated from the choice of "Wear". They quantified the price of Wear using hedonic price regressions, and both VMT and Wear became continuous variables in the utility function. The joint model was implemented on the same CEX dataset as Fullerton and Gan (*6*), supplemented with the corresponding OVB (Owned Vehicle Part B Detailed questions) and information on miles per gallon (MPG) of new vehicles from the EPA's report, emissions per mile (EPM) from the CARB, and gas prices from the ACCRA cost of living indexes. The authors concluded that short-run price elasticity for continuous variables like VMT are smaller than long-run elasticity for discrete choices. Thus, for instance, a tax on age of SUV might reduce emissions both by inducing a switch from SUVs to cars and by inducing a switch from older SUVs to newer SUVs.

Davis and Kilian (*48*) pointed out that the adoption of a carbon tax often fails to address two important problems: (a) the endogeneity of gasoline prices and (b) the responsiveness of gasoline consumption to a change in tax may differ from those to an average change in price. Their models successfully overcame these challenges by using traditional single-equation regression models, estimated by least squares or instrumental variables methods, and structural vector auto-regressions. Their results showed that an additional 10 cent gasoline tax per gallon would reduce vehicle carbon emission by about 1.5% in the United States.

Musti and Kockelman (*7*) used a multinomial logit model to estimate vehicle class for 596 households and a regression to estimate vehicle usage (VMT) on a subsample from the 2001 NHTS dataset. EPA (*43*) conversion factors and fuel economy assumptions were used to translate VMT into GHGEs. Their research was based on the assumptions that (a) a gallon of gasoline was assumed to produce 11.52 kg (or 25.4 lb) of CO_2 and (b) automobiles emitted methane (CH_4) and nitrous oxide (N_2O) from the tailpipe, as well as hydro-fluorocarbons (HFC) emissions from leaking air conditioners (*38*). The study concluded that in the long run, gas price dynamics, tax incentives, purchase prices, along with new technologies, government-industry partnerships, range and recharging times should have added effects on energy dependence and greenhouse gas emissions.

Vyas et al. (*4*) took advantage of Bhat's MDCEV (*31*) model framework and proposed a joint MDCEV- multinomial logit (MNL) model to estimate the number of vehicles owned by the household, vehicle type, annual mileage on each vehicle and the individual assigned as the primary driver for each vehicle. The joint model was applied on household information from 2008 California Vehicle Survey data (*49*) collected by the California Energy Commission. The most significant contribution from the research was that the estimated vehicle type and ownership served as the engine for a household vehicle composition and evolution simulator which is embedded in the larger activity-based travel and emissions forecasting system - SimAGENT (the Simulator of Activities, Greenhouse Emissions, Energy, Networks, and Travel) (*50*). To the authors' knowledge, this was the first effort to integrate a complete household vehicle ownership and type choice simulator into a larger activity-based model micro-simulator system.

Haultfoeuille et al. (*51*) developed a demand model that combined household vehicle ownership and annual mileage with households' heterogeneity in preferences. They estimated the market shares of new automobiles on the exhaustive dataset of the registration of new cars from January 2003 to January 2009 provided by the Association of French Automobile Manufacturers (CCFA). In order to test the short-run and long-run effects on CO_2 emissions from vehicles, the authors took into account elements of the composition of the vehicle fleet, VMT and the production of vehicles. However, the impact of vehicle-related policy indicated that French households had reacted strongly to financial incentives.

Table 2-2 below summarizes the studies on household vehicle emissions using joint discrete-continuous models and their corresponding applications.

TABLE 2 - 3 Summary of Emissions Estimation by Integrated Car Ownership Models

Authors (Year)	Data	Joint Model	Emissions	Policy	Results
Hayashi et al. (2001)			GHGEs	Car purchase tax, car ownership tax, car usage tax	Impact from usage tax, ownership tax and purchase tax is in decreasing order
Fullerton et al. (2005)	aggregated data set from 47 prefectures in Japan	Vehicle ownership and driving distance	CO2 emissions	Tax on engine size, emission rate, vehicle age, unit of CO2, liter of gasoline, kilometer driven	Impact from fuel tax are greater than taxes on vehicle characteristics
Fullerton and	CARB, 1996-	vehicle	Vehicle	Vehicle-related	Fuel tax is the most cost-

Gan (2005)	2001 CEX, ACCRA	quantity, type and VMT	emissions	taxes	effective among all tested taxes
Feng et al. (2005-2013)	1996-2001 CEX, OVB, ACCRA	Vehicle quantity, age and VMT	Vehicle emissions	Vehicle purchase tax and fuel tax	Short-run price elasticities for continuous variables are smaller than long-run elasticities for discrete choices
Davis and Kilian (2009)	For households of the United States		Carbon emissions	Vehicle purchase tax and fuel tax	additional 10 cent gasoline tax per gallon would reduce vehicle carbon emissions by about 1.5%
Musti and Kockelman (2011)	2001 NHTS, EPA (2007) conversion factors	Vehicle class and usage	GHGEs		GHGEs are affected by gas price, tax incentives, purchase price, government-industry, range, recharge time
Vyas et al. (2012)	2008 California Vehicle Survey data	Vehicle quantity, age and VMT, primary driver	GHGEs		Successfully integrate the joint model into SimAGENT
Haultfoeuille et al. (2013)	registration of new cars from January 2003 to January 2009 from CCFA	Vehicle ownership and annual mileage	CO2 emissions	Vehicle-related policy	French households have reacted strongly to financial incentives created by the policy

**note: "CEX" represents the Consumer Expenditure Survey, "CARB" represents the California Air Resources Board, "OVB" is Owned Vehicle Part B Detailed questions , "CCFA" represents French Automobile Manufacturers, "SimAGENT" represents the Simulator of Activities, Greenhouse Emissions, Energy, Networks, and Travel.*

Chapter 3: Proposed Model System: Methodology

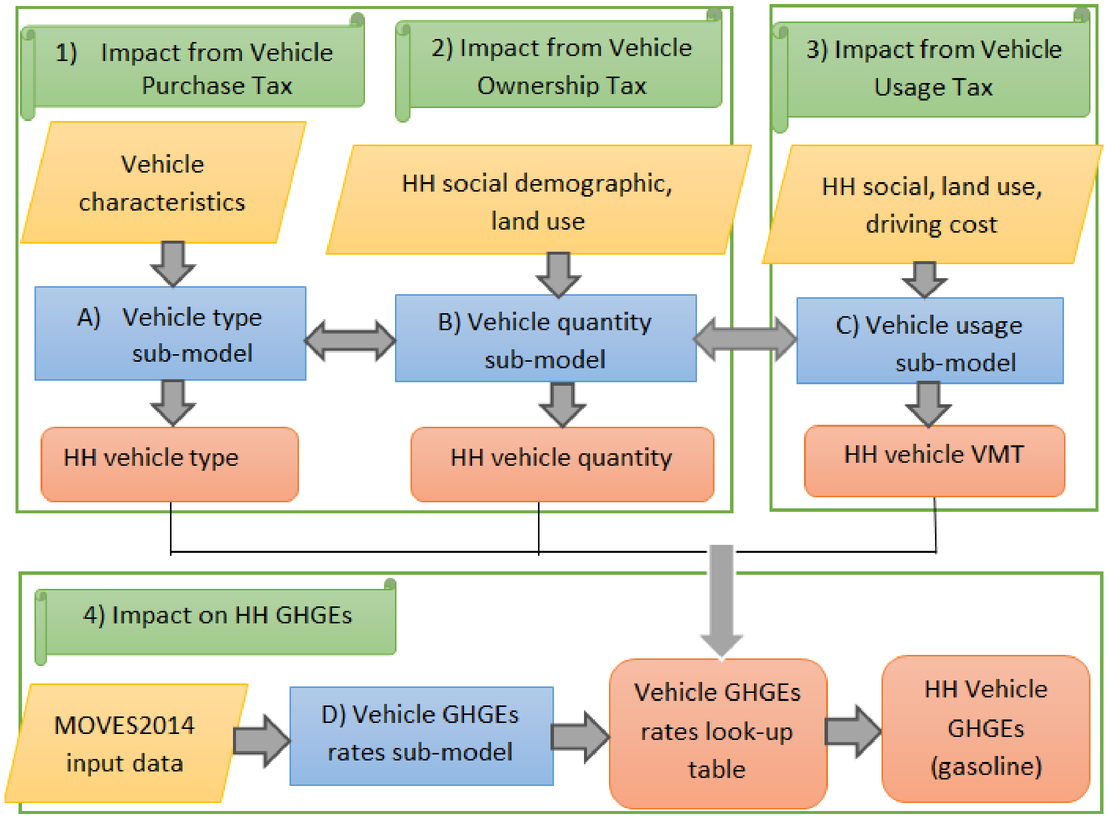
3.1 Proposed Model System for Vehicle GHGEs

A model system is developed based on consumers' car purchasing and usage behavior, as well as governments' sustainable call to reduce GHGEs. The system includes four sub-models: (1) vehicle type and vintage logit model, (2) vehicle quantity probit model, (3) car usage regression and (4) vehicle GHGEs rates model. In this part, we will introduce the structure, input attributes and outputs of each sub-model.

3.1.1 Structure of the Model System

The structure of the proposed model system is illustrated in Figure 3-1. An integrated car ownership model, involving the first three sub-models, has been employed to estimate household vehicle type and vintage, quantity and usage which serve as inputs for vehicle GHGEs calculation. In the vehicle GHGEs rates sub-model, we use MOVES to estimate emission rates for six different types of gasoline vehicles. In Figure 3-1, HH represents household, yellow represents inputs, blue represents sub-models and red represents outputs.

FIGURE 3 - 1 Structure of the model system.



3.1.2 Inputs and Outputs of the Model System

A supplementary table (Table 3-1) highlights input and output attributes for the four sub-models. Vehicle characteristics, household social demographic and land use variables are the main attributes for the model system. In Table 3-1, AVMT represents annual VMT.

TABLE 3 - 1 Sub-models Input-Output Table

SUB-MODELS	INPUTS		OUTPUTS
	Variable Category	Parameters	
Vehicle Type and vintage Sub-model	Vehicle characteristics	Purchase price Shoulder room Luggage capacity Average MPG Vehicle make/model Model year	Estimated vehicle type distribution Logsum of vehicle type
Vehicle Quantity	HH socio-demographic	Income	Estimated HH vehicle

Sub-model	Land use	Number of drivers HH head gender Residential density Vehicle type logsum	quantity
Vehicle Usage Sub-model	Vehicle VMT and cost HH socio-demographic Land use	Income HH head gender Residential density Fuel/Travel cost	Estimated vehicle AVMT
Vehicle Emission Rate Sub-model	Vehicle characteristics Regional traffic conditions	Vehicle type Vehicle ownership Vehicle VMT Vehicle age Vehicle speed Vehicle population Fuel type Repair frequency Local meteorology Road type	Vehicle emission rates To calculate vehicle annual GHGEs To calculate HH annual GHGEs

3.2 Vehicle Type and Vintage Sub-Model

3.2.1 Vehicle Type Sub-model

The vehicle type sub-model is designed to forecast households' preferences on different vehicle types and vintages. We consider two possible vehicle types: passenger car and passenger truck; and three vintages: (a) model year from 2006 to 2009 (not older than 3 years); (b) model year from 2003 to 2005 (between 3 and 6 years old) and (c) model year before 2003 (older than 6 years). A series of multinomial logit models are employed to determine the preferences on vehicle types and vintages for households holding different numbers of vehicles. For one-vehicle households, they can choose from 6 alternatives; two-vehicle households can choose among 6 x 6 different combinations of alternatives, and finally, three-vehicle households have a choice set composed by 6 x 6 x 6 alternatives. Because of the large number of alternatives for households with more than one vehicle, estimation on the full set of alternatives has been considered infeasible, even for the multinomial logit model. However, taking advantage of the independence of irrelevant alternative (IIA) property, the logit model can be estimated based on a subset of randomly chosen alternatives plus the chosen alternative. According to Train (*24*), beyond a minimal number of alternatives, the estimated parameters are not sensitive to the number of alternatives included in estimation. Therefore, for two-vehicle households, a subset of 10 randomly selected alternatives is obtained including the one chosen by the household. For three-vehicle households, the number of randomly selected alternatives in the subset is 20, including the one chosen by the household. The formulation of vehicle type and vintage model is presented as follows:

$$U_{t_N|N,in} = {X_{t_N|N,ijn}}^T \beta_{t_N|N,jn} + \varepsilon_{t_N|N,in} \quad , \quad \varepsilon_{t_N|N} \sim_{iid} EV1(0,\lambda) \quad , \quad N = 1,2,3$$

Equation 3 - 1

Where $U_{t_N|N,in}$ is the utility of household n choosing type i among t_N different vehicle types, conditioned on the household having N vehicles; $X_{t_N|N,ijn}$is the value of attribute j, $\beta_{t_N|N,jn}$represents the coefficient of attribute j; $\varepsilon_{t_N|N,in}$is the unobserved error term which follows an extreme value type 1 distribution. λ is a scale parameter and *T* is for transpose. The deterministic part of utility can be represented as follows:

$$V_{t_N|N,in} = {X_{t_N|N,ijn}}^T \beta_{t_N|N,jn}$$

Equation 3 - 2

The MNL choice probability has a closed form and only depends on utility differences. Therefore, the probability function can be computed as follows:

$$P_{t_N|N,in} = \frac{1}{\sum_{i'} exp\lambda^{-1}(V_{t_N|N,i'n} - V_{t_N|N,in})}$$

Equation 3 - 3

In this case, it is impossible to identify β, but $\lambda^{-1}\beta$ can be identified. Although λ does not affect the ratio of any two parameters, it needs to be normalized to 1. The covariance matrix of the normalized model $\Sigma_{t_N|N} = \frac{\pi^2}{6} I_{t_N|N}$, where $I_{t_N|N}$ is the identity matrix of size t_N.

3.2.2 Calibration of Logsum

The expected maximum utility of choosing vehicle types, logsum, is generally obtained to describe households' benefits deriving from diverse vehicle types. The logsum can be written as:

$$L_{N,n} = ln \sum_{i=1}^{t_N|N} \exp(V_{t_N|N,in})$$

Equation 3 - 4

Where $L_{N,n}$is the expected maximum utility for household n who has N vehicle. The logsum will be utilized in the vehicle ownership sub-model later.

3.3 Vehicle Quantity Sub-Model

The method to forecast households' vehicle quantity is derived from the one proposed by Train (*24*), Cirillo and Liu (*52*) and Liu et al. (*3*). It basically combines the vehicle type and vintage model and the quantity model by assuming that households choose vehicle type and vintage conditioned on the number of vehicles held by the households. In the vehicle quantity sub-model, a multinomial probit model with four alternatives – households with 0, 1, 2 and 3 vehicles, is adopted. The attributes we considered are mainly household social demographic and land use variables.

$$U_{N,in} = V_{N,in} + \alpha V_{t_N|N,in} + \varepsilon_{N,in} \ , \quad \varepsilon_{N,in} \ \sim_{iid} N(0,\ \Sigma\ ) \ , \quad N = 0, 1, 2, 3$$

Equation 3 - 5

Where $V_{N,in}$ represents the utility of household n who holds N vehicles choosing alternative i; $V_{t_N|N,in}$ is the utility of choosing vehicle type and vintage t_N conditional on holding N vehicles; α is a parameter to be estimated; $\varepsilon_{N,in}$ is the error term that follows a normal distribution. The number of alternatives in t_N varies depending on the number of cars owned by the household (see Section 3.2.1). Alternatively, the conditional utility$V_{t_N|N,in}$ can be rewritten as a function of the *logsum* of the vehicle type model.

$$U_{N,in} = X_{N,ijn}{}^T \beta_{N,jn} + \alpha L_{N,n} + \varepsilon_{N,in} \ , \quad \varepsilon_{N,in} \ \sim_{iid} N(0, \Sigma) \ , \quad N = 0, 1, 2, 3$$

Equation 3 - 6

Where $X_{N,ijn}$ is the value of attribute j; $\beta_{N,jn}$ is the coefficient corresponding to attribute j. More specifically, the utility function of each alternative in our model can be expressed as follows:

$$U_{0,in} = \varepsilon_{0,in}$$

Equation 3 - 7

$$U_{1,in} = V_{1,in} + \alpha L_{1,n} + \varepsilon_{1,in}$$

Equation 3 - 8

$$U_{2,in} = V_{2,in} + \alpha L_{2,n} + \varepsilon_{2,in}$$

Equation 3 - 9

$$U_{3,in} = V_{3,in} + \alpha L_{3,n} + \varepsilon_{3,in}$$

Equation 3 - 10

Where $U_{0,in}, U_{1,in}, U_{2,in}, U_{3,in}$ represent the utility of household n who has 0, 1, 2 and 3 vehicles respectively, choosing alternative i.

The decision maker is assumed to be rational and he or she will choose the alternative according to the utility maximization method. In this model, we assume the error terms of the probit model follow a multivariate normal distribution with a full, unrestricted, covariance matrix. Originally, the size of the covariance matrix is $\mathrm{J} \times \mathrm{J}$ and there are $[\mathrm{J} \times (\mathrm{J}+1)]/2$ different elements to be estimated, where J is the number of alternatives. For the reasons that only utility differences can be identified, the covariance matrix of the model after taking differences with respect to zero-car group is as follows:

$$\widetilde{\Sigma_0} = \Delta_0 \Sigma \Delta_0'$$

Equation 3 - 11

$$\Delta_0 = \begin{bmatrix} -1 & 1 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ -1 & 0 & 0 & 1 \end{bmatrix}$$

Equation 3 - 12

Where $\Sigma_0^{\sim}$ has $[\mathrm{J} \times (\mathrm{J}-1)]/2$ different elements subjected to identification normalizations. The first element of the $\Sigma_0^{\sim}$ diagonal can be normalized to 1, and the number of identified parameters is reduced to $[\mathrm{J} \times (\mathrm{J}-1)]/2 - 1$. In the proposed model, the number of alternatives equals 4 which indicates that there are 5 different elements to be estimated after taking utility differences and performing the normalization. To be more specific, the estimable model after taking the difference utility can be written as follows for simplicity:

$$\Delta_0 U_{in} = \Delta_0 X_{in}{}^T \beta + \Delta_0 \varepsilon_{in}$$

Equation 3 - 13

Where $\Delta_0 U_{in}$ is the utility difference between households holding one, two and three cars and households held zero car. According to the difference function, the probability of choosing alternative i can be expressed as follows:

$$P_{in} = \Pr\left(\Delta_0 U_{in} > \Delta_0 U_{jn}, \forall\, j \in C_J, j \neq i\right)$$
$$= \Pr(\Delta_0\left(V_{in} - V_{jn}\right) > \Delta_0\left(\varepsilon_{jn} - \varepsilon_{in}\right), \forall\, j \in C_J, j \neq i)$$

Equation 3 - 14

Where C_J represents the whole choice set. The probability of choosing alternative i equals the probability that alternative i has the maximum utility after taking differences for household n. Noting that the utility after taking differences for the zero-car group is normalized to be zero, the probability of a household choosing to have zero cars is the simplest case to be expressed.

$$\begin{aligned} P_{0n} = \Pr\left(0 > \Delta_0 U_{jn}, \forall\, j \in C_J, j > 0\right) &= \Pr(-\Delta_0 V_{jn} > \Delta_0 \varepsilon_{jn}, \forall\, j \in C_J, j > 0) \\ &= \int_{-\infty}^{-\Delta_0 V_{(J-1)n}} \cdots \int_{-\infty}^{-\Delta_0 V_{1n}} f(\Delta_0 \varepsilon_n) d(\Delta_0 \varepsilon_n) \\ &= F_{\Delta_0 \varepsilon_n}(-\Delta_0 V_{1n}, \dots, -\Delta_0 V_{(J-1)n}) \end{aligned}$$

Equation 3 - 15

Where $f(\Delta_0 \varepsilon_n) = \frac{1}{(2\pi)^{\frac{1}{2}(J-1)} |\tilde{\Sigma}_0|^{\frac{1}{2}}} \exp\{-\frac{1}{2}\, \varepsilon_n{}' \Delta_0{}' \widetilde{\Sigma_0} \Delta_0 \varepsilon_n\}$. It can be observed that the probability function is equivalent to (J-1)-dimensional integrals over the differences between error terms. There is no closed-form expression for this integral. Maximum log-likelihood is the preferred method for obtaining optimal coefficients.

3.4 Vehicle Usage Sub-Model

3.4.1 Regressions

In the usage sub-model, regressions are adopted to estimate how the annual vehicle miles traveled (AVMT) of households with 1, 2 and 3 vehicles are influenced by households' social demographic, land use and travel cost variables. In order to estimate the AVMT for each vehicle within households, three regressions are proposed to predict the usage patterns for households' primary, secondary and tertiary vehicles. In each regression, the dependent variable $Y_{reg,s}$ is assumed to be a linear combination of a vector of predictors $X_{reg,s}$ and a multivariate normal error term $\varepsilon_{reg,s}$.

$$Y_{reg,s} = X_{reg,s}^T \beta_{reg,s} + \varepsilon_{reg,s} \;, \quad \varepsilon_{reg,s} \sim N(0, \sigma_s^2)$$

Equation 3 - 16

Where $s \in \{1st, 2nd, 3rd\}$. Usually, regressions are solved by the Ordinary Least Squares (OLS) estimator [Weisberg, 2005], but the problem can also be expressed in the form of a likelihood function to be maximized [McCulloch et al., 2008, p. 117].

For N-car households, given

$$Y_{reg} = (Y_{reg,1st}, Y_{reg,2nd}, \dots, Y_{reg,nth})$$

Equation 3 - 17

$$X_{reg} = (X_{reg,1st}, X_{reg,2nd}, \dots, X_{reg,nth})$$

Equation 3 - 18

$$\beta_{reg} = (\beta_{reg,1st}, \beta_{reg,2nd}, \dots, \beta_{reg,nth})$$

Equation 3 - 19

$$\varepsilon_{reg} = \left(\varepsilon_{reg,1st}, \varepsilon_{reg,2nd}, \dots, \varepsilon_{reg,nth}\right) \sim N(\mathbf{0}, \Sigma_{reg,n})$$

Equation 3 - 20

$$\Sigma_{reg,n} \textit{is the covaraince matrix of size } n \times n$$

The likelihood of observing Y_{reg} is given by the multivariate normal density function:

$$\mathrm{P}\left(Y_{reg} \middle| X_{reg}, \beta_{reg}, \Sigma_{reg,n}\right) = \varphi(Y_{reg} | X_{reg}^T \beta_{reg}, \Sigma_{reg,n})$$

Equation 3 - 21

Where y_{reg} is a set of observed AVMT of certain household; n is the number of vehicles within households. Correspondingly, the AVMT of one-car households follows a normal distribution centered at $X_{reg,1st}^T \beta_{reg,1st}$ and has a variance $\sigma_{reg,1st}^2$. The AVMT of two-car and three-car households follow multivariate normal distributions, and the size of their covariance matrices are 2×2 and 3×3 , respectively.

$$\Sigma_{reg,2} = \begin{bmatrix} \sigma_{reg,1st}^2 & \sigma_{reg,1st,2nd} \\ \sigma_{reg,2nd,1st} & \sigma_{reg,2nd}^2 \end{bmatrix}$$

Equation 3 - 22

$$\Sigma_{reg,3} = \begin{bmatrix} \sigma_{reg,1st}^2 & \sigma_{reg,1st,2nd} & \sigma_{reg,1st,3rd} \\ \sigma_{reg,2nd,1st} & \sigma_{reg,2nd}^2 & \sigma_{reg,2nd,3rd} \\ \sigma_{reg,3rd,1st} & \sigma_{reg,3rd,2nd} & \sigma_{reg,3rd}^2 \end{bmatrix}$$

Equation 3 - 23

3.4.2 Endogeneity and Instrumental Variables Method

In a statistical model, the explanatory variables are said to be endogenous when they are correlated with the unobserved factors. In a regression model, $\mathbf{y} = \beta\mathbf{x} + \varepsilon$, the coefficients estimated by the Ordinary Least Squares (OLS) method will be biased due to endogeneity. More specifically, if there is correlation between x and ε, both a direct effect via β x and an indirect effect via ε effecting x which will in turn affect the dependent variable y when estimating β. The goal of the regression is to estimate the first effect. However, the OLS estimator of β will instead combine the two effects, giving OLS(β) > β if both effects are positive. The formulation can be illustrated as follows:

$$\text{Given } \mathbf{y} = \beta\mathbf{x} + \varepsilon(\mathbf{x})$$

Equation 3 - 24

$$\mathrm{OLS}(\beta) = \frac{dy}{dx} = \beta + \frac{d\,\varepsilon(\mathrm{x})}{dx} > \beta$$

Equation 3 - 25

The OLS estimator is therefore biased and inconsistent for β, unless there is no association between x and ε. The magnitude of the inconsistency of OLS is $(X'\mathrm{X})^{-1}X'\varepsilon$.

Generally, endogeneity derives from measurement error, auto-regression with auto-correlated errors, simultaneity, omitted variables, and sample selection errors. The following three examples describe three typical cases of endogeneity respectively: (a) unobserved attributes of a product can affect its price; (b) marketing efforts can be related to prices; and (c) the interrelated choices of decision makers (*53*). In a car purchasing market, the price of a vehicle is considered to be an endogenous variable because it is determined by both observed attributes such as the fuel efficiency, length, width horsepower, weight and unobserved attributes such as comfort, beauty of design, smoothness of the ride, and expected resale value. Another case is marketing efforts such as advertising and sales promotions that cannot be measured directly by researchers. The correlations between price and the unobserved terms can be either positive or negative. The third example illustrates the interrelated choices of decision makers, like travel mode and house location. From statistical results, people living in urban areas prefer to use public transportation more than those living in suburban or rural areas.

The inconsistency of OLS is due to endogeneity of x, indicating that the changes in x are associated not only with the changes in y but also changes in the error term ε. An instrumental variable (IV) z, which has the property that changes in z are associated with changes in x but does not directly lead to changes in y, is generally introduced to avoid the inconsistency problem. More formally, an IV z for the regressor x in a regression model must fulfill the following: (a) z is uncorrelated with the error term ε and (b) z is correlated with x. The first assumption excludes the IV z from being an explanatory variable in the model for y, because if y depends on both x and z instead of depending only on x, z will be absorbed into the error term ε. The second assumption requires that there is some association between the instrument and the variable being instrumented.

A two-stage least-squares (2SLS or TSLS) method is employed to calculate IV estimators and then to estimate unbiased coefficients for the regression. The two stages are (a) regress endogenous variable x on exogenous regressors using OLS and obtain estimated $\hat{x}$ and (b) regress dependent variable y on $\hat{x}$ and other explanatory variables using OLS.

In our vehicle usage regression, the instrumental variable method is employed to avoid the endogeneity of the driving cost variable. This method is required because when households choose the type and vintage of vehicles, they effectively choose the driving cost of those vehicles (*24*). Therefore, the driving cost, considered as an endogenous variable, is regressed on the exogenous variables including household income, number of drivers, number of workers, owned or rental house, dummy of urban area, urban size, age of the household' head and the education level of the household head. The predicted values from these regressions are obtained and used as exogenous variables in the vehicle usage regression.

3.5 Integrated Discrete-Continuous Choice Model

In real life, households usually decide to buy certain types of vehicles according to the quantity of owned vehicles and the future usage of the new one. In other words, the decisions of vehicle type, quantity and usage are determined simultaneously instead of sequentially. In our framework, the model accounts for the correlation between the discrete part of vehicle type and quantity and the continuous part of vehicle usage, which corresponds to reality. In econometrics, there are two ways to calculate the joint probability of vehicle quantity and usage. Given that Y_{disc} and Y_{reg} represent the dependent variables of discrete part and continuous part respectively, the joint probability can be written in the following two forms:

$$P(Y_{disc}, Y_{reg}) = P(Y_{reg})P(Y_{disc} \mid Y_{reg})$$

Equation 3 - 26

The joint probability of observing Y_{disc} and Y_{reg} is the product of the probability of observing Y_{reg} and the probability of observing Y_{disc} conditional on Y_{reg}.

$$P(Y_{disc}, Y_{reg}) = P(Y_{disc})P(Y_{reg} \mid Y_{disc})$$

Equation 3 - 27

Alternatively, the joint probability of observing Y_{disc} and Y_{reg} is the product of the probability of observing Y_{disc} and the probability of observing Y_{reg} conditional on Y_{disc}. This is a general result about conditioning with random variables [Rice, 2007, p.88]. Comparing the simulation results between the above two methods to obtain the joint probability, the former turns out to be a better approach for constructing the integrated model (*54*).

Technically, we combine the formulations of the vehicle quantity model and the vehicle usage model. Because the unobserved error terms of both models follow a normal distribution centered at zero, a multivariate normal (MN) distribution therefore corresponds to the error term of the integrated model. Specifically, due to identification purposes, we use the differences of error terms from the vehicle quantity probit model. Thus, the dimension of the discrete part is: 4 (the number of alternatives) – 1 (the base alternative for normalization). In terms of the vehicle usage model, the dimension of the continuous part varies among households holding different numbers of vehicles, and the dimension of the continuous part for a household holding n vehicles is n. For example, if a household owns two vehicles, the dimension of the covariance matrix of the continuous part is 2 (see 3.4.1). In conclusion, the dimension of the MN distribution for households holding n vehicles is: 3 (number of alternatives - 1) + n.

$$\left(\widetilde{\varepsilon_1}, \widetilde{\varepsilon_2}, \widetilde{\varepsilon_3}, \widetilde{\varepsilon_{reg,n}}\right) \sim MN(\mathbf{0}, \Sigma_{3+n})$$

Equation 3 - 28

Where $\widetilde{\varepsilon_j} = \varepsilon_j - \varepsilon_0$ $(j = 1, 2, 3)$ representing the differences of error terms relative to the base ε_0. The reason is that only utility difference of alternatives matters.

To obtain the joint probability $\mathrm{P}\left(Y_{disc}, Y_{reg}\right)$, we should first calculate $\mathrm{P}\left(Y_{reg}\right)$ and $P(Y_{disc} \mid Y_{reg})$. The probability of observing Y_{reg} is given in 3.4.1, which can be alternatively written as follows:

$$\mathrm{P}\left(Y_{reg}\right) = \varphi\left(\varepsilon_{reg} \middle| \mu = \mathbf{0},\ \Sigma = \ \Sigma_{reg}\right),\ \ \varepsilon_{reg} = Y_{reg} - \widetilde{Y_{reg}}$$

Equation 3 - 29

The probability of observing Y_{disc} conditional on observing that Y_{reg} follows a conditional multivariate normal distribution. If (A, B) follow a multivariate normal distribution with mean μ and variance **Σ** where:

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}$$

Equation 3 - 30

$$\Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}$$

Equation 3 - 31

$$\begin{bmatrix} A \\ B \end{bmatrix} \sim MN(\mu, \Sigma)$$

Equation 3 - 32

Then the conditional distribution (A|B) follows a multivariate normal distribution with a new mean μ_A and variance Σ_A:

$$\mu_{A|B} = \mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(B - \mu_2)$$

Equation 3 - 33

$$\Sigma_{A|B} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$$

Equation 3 - 34

Similarly, considering $\mathrm{A} = \tilde{\varepsilon_j}$ and $\mathrm{B} = \varepsilon_{reg}$, $(\tilde{\varepsilon_j}, \varepsilon_{reg})$ follows a multivariate normal distribution with mean $\mu_{d-r}$and variance $\Sigma_{d-r}$where

$$\mu_{d-r} = \begin{bmatrix} \mu_{disc} \\ \mu_{reg} \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \end{bmatrix}$$

Equation 3 - 35

$$\Sigma_{d-r} = \begin{bmatrix} \Sigma_{disc} & \Sigma_{disc,reg} \\ \Sigma_{reg,disc} & \Sigma_{reg} \end{bmatrix}$$

Equation 3 - 36

$$\begin{bmatrix} \tilde{\varepsilon_j} \\ \varepsilon_{reg} \end{bmatrix} \sim MN(\mu_{d-r}, \Sigma_{d-r})$$

Equation 3 - 37

Where $\Sigma_{reg}$is reduced to σ_{reg}^2 for one vehicle households. Then, the conditional distribution $(\tilde{\varepsilon_j} \mid \varepsilon_{reg})$ follows a multivariate normal distribution with new mean $\mu_{d|r}$and variance $\Sigma_{d|r}$:

$$\mu_{d|r} = \mu_{disc} + \Sigma_{disc,reg}\Sigma_{reg}^{-1}(\varepsilon_{reg} - \mu_{reg}) = 0 + \Sigma_{disc,reg}\Sigma_{reg}^{-1}(\varepsilon_{reg} - 0)$$

Equation 3 - 38

$$\Sigma_{d|r} = \Sigma_{disc} - \Sigma_{disc,reg}\Sigma_{reg}^{-1}\Sigma_{reg,disc}$$

Equation 3 - 39

The conditional distribution of the discrete part can be represented as:

$$P(Y_{disc} \mid Y_{reg}) = P(\widetilde{\varepsilon_j} \mid \varepsilon_{reg}) = \int_{R^{J-1}} f\left(\widetilde{V_{ij}} + \widetilde{\varepsilon_{ij}} < 0, i \in C_j, i \neq j\right) \varphi(\widetilde{\varepsilon_j}) d\widetilde{\varepsilon_j}$$

Equation 3 - 40

Where $\varphi(\widetilde{\varepsilon_j})$ is the density function of a multivariate normal distribution with mean $\mu_{d|r}$ and variance $\Sigma_{d|r}$; $\widetilde{V_{ij}}$ represents the utility difference of the deterministic part between alternative i and j; $\widetilde{\varepsilon_{ij}}$ represents the difference of error term between alternative i and j; (J-1) is the dimension of the integral.

3.6 Vehicle GHGEs Rates Sub-model

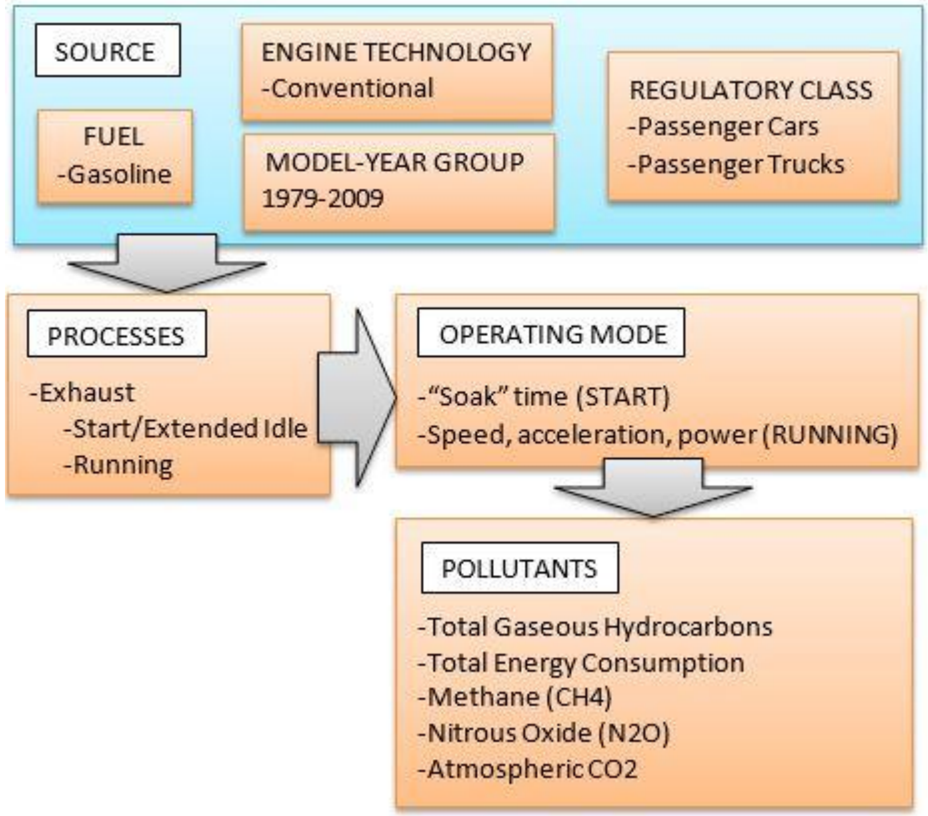
The vehicle GHG Emission Rates sub-model is the core part of our vehicle GHG emission estimator. In this part, the emission rates of the main components of GHG will be estimated for different vehicle type and vintage combinations. The main components of vehicle GHG are carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) from the tailpipe and hydro-fluorocarbon (HFC) from leaking air conditioners. The emissions of the latter three gases are small in comparison to CO_2. However, these gases have a higher global warming potential than CO_2 (*55*). To be consistent with the vehicle type sub-model (see 3.2.1) and vehicle classifications in MOVES (Motor Vehicle Emission Simulator), there are a total of six vehicle type and vintage combinations. Because the evaporation process does not emit GHG, the vehicle emission rates are mainly estimated during two processes: (a) running process; and (b) start and extended idle process. For comparison purposes, the emissions of all GHG components will be transformed into carbon dioxide equivalent (CO_2E).

3.6.1 MOVES Software

EPA's Office of Transportation and Air Quality (OTAQ) has developed the Motor Vehicle Emission Simulator (MOVES). This emission modeling system estimates emissions for mobile sources covering a broad range of pollutants and allows multiple scale analysis. In MOVES, a run specification (Run Spec) and the input database are necessary to describe a target zone and its traffic condition. A run specification contains a scenario description, scale, inventory or emission rates, time spans, geographic bounds, vehicles or equipment, road type, pollutants and processes and output. The three scales in MOVES are nation-level, county-level and project-level. The Washington D.C. Metropolitan Area spans four states - District of Columbia, Maryland, Virginia and West Virginia, encompassing eighteen counties. Thus, we choose the scale of county-level in the run specification. In order to forecast GHGEs for each household in the target area, "emission rates" should be chosen instead of "inventory". For time spans, two scenarios are determined for a typical summer month – July and a typical winter month – January, respectively. The pollutants we are interested in are CO_2, CH_4 and N_2O, and their emission rates have been transformed into CO_2E.

To be specific, a flowchart to illustrate how to estimate emission rates of CO_2, CH_4 and N_2O in terms of source, processes, operating mode and pollutants is presented as follows:

FIGURE 3 - 2 Estimation Rates Estimation Flowchart.



Operating modes for running emissions are based primarily (but not entirely) on "vehicle specific power" (VSP, kW/Mg). VSP represents a vehicle's tractive power normalized to its own weight. VSP is calculated as a function of velocity, acceleration, weight and the vehicles' road-load coefficients. The MOVES workshop provides the formulation as follows:

$$VSP_t = \frac{Av_t + Bv_t^2 + Cv_t^3 + mv_t a_t}{m}$$

Equation 3 - 41

Where v = velocity, m/sec

a = acceleration, m/sec^2

m = weight (metric ton)

A = rolling resistance (kW-sec/m)

B = rotating resistance (kW-sec^2/m^2)

C = aerodynamic drag (kW-sec^3/m^3)

Operating modes for start emissions are defined in terms of "soak" time, representing a period of time since the engine was turned off, before being restarted.

3.6.2 Inputs and Outputs

The input database, which corresponds to the run specification, contains ten data files: (a) source type population; (b) vehicle type VMT; (c) maintenance (I/M) programs; (d) fuel type and technology; (e) fuel and formulation; (f) meteorology; (g) ramp fraction; (h) road type distribution; (i) age distribution and (j) average speed distribution. The source types considered are passenger car and passenger truck, which are the main vehicle type holdings by households in the Washington D.C. Metropolitan Area. To prepare the data of vehicle type VMT, we use MOVES input VMT calculator which estimates monthly, daily and hourly VMT fractions in the target region. Meteorology data describes temperature and humidity for each hour in a 24-hour scale. Road type data illustrates the VMT distribution on five road types – off-network, rural restricted access, rural unrestricted access, urban restricted access and urban unrestricted access. The average speed in MOVES has been categorized into 16 bins ranging from speeds less than or equal to 2.5 mph to speeds greater than or equal to 72.5 mph. The data provides the average speed distribution of the whole vehicle population over the 16 speed bins. Our input data are mainly derived from the 2009 NHTS, *American Fact Finder*, the 2009 SMVR by the Federal Highway Administration (FHWA) and MOVES default data.

In emission rates mode, MOVES outputs three rate tables that cover all the emissions processes, namely, "Rateperdistance", "Ratepervehicle" and "Rateperprofile", which provide emissions during running, start and extended idle and resting evaporation processes respectively. In addition, there are sub-processes in each of the three main processes. All the sub-processes and their IDs are defined by the EPA listed in Table 3-2.

TABLE 3 - 2 MOVES Output Table: Rates for Each Process

MOVES Output Table	Process and ID
Rateperdistance – Running emissions	Running exhaust Brake wear Tire wear Evap permeation Evap fuel vapor venting Evap fuel leaks Crankcase running exhaust Refueling displacement vapor loss Refueling spillage loss
Ratepervehicle - Start emissions	Start exhaust Crankcase start exhaust
Ratepervehicle - Extended idle emissions	Crankcase extended idle exhaust Extended idle exhaust
Rateperprofile - Resting evaporative emissions	Evap permeation Evap fuel vapor venting Evap fuel leaks

The output databases we mainly use are "Ratepervehicle" and "Rateperdistance", which provide both vehicle start/extended idle emission rates (grams per vehicle) and running emission rates (grams per vehicle per mile) for the interested pollutants. According to the estimated vehicle type sub-model (See 3.2.1), the households' vehicles are classified into six categories based on different sizes and vintages. Therefore, for each category, the emission rates can be calculated by getting weighted averages of speed bins, road types and temperatures.

3.6.3 Emission Rates Calculation

All of the results of a MOVES RunSpec are stored in MySQL database tables. These results can be accessed via MySQL query commands, the MySQL query browser, MySQL workbench. or Microsoft Access with MySQL Open Database Connectivity (ODBC). Data in ".sql" form can be transformed directly into ".csv", ".xls" or "xlsx" forms by the above MySQL software.

According to the emission rates output table, the running rates vary with temperature, road type and speed bin. The number of running rates produced is the summation of the number of source types, the number of sub-processes, 4 road types, 16 speed bins and the number of temperatures. To calculate the emission rates for each source type during the entire running process, we first calculate the weighted average over 4 road types, 16 speed bins and different temperatures, and then take the summation of emission rates of sub-processes under each combination of road type, speed bin and temperature.

Similarly, the start and extended idle rates vary with temperature, type of day (weekday or weekend day) and hour of day. The number of the rates produced is the summation of the number of source types, the number of sub-processes, the number of temperatures, 2 day types and 24 hours. To calculate the emission rates for each source type during the start and extended idle processes, we first calculate the weighted average over 2 day types, 24 hours and different temperatures, and then take the summation of emission rates of sub-processes under each combination of day type, hour of day and temperature.

The resting evaporative rates also vary with temperature, type of day (weekday or weekend day) and hour of day. The number of the rates produced is the summation of the number of source types, the number of sub-processes, the number of temperature, 2 day types and 24 hours. Due to the small resting evaporative rates, we will not take this part into consideration in our model system. Table 3-3 provides a summary of how emission rates vary.

TABLE 3 - 3 How Output Rates Vary

Rates vary with (num.)	Rateperdistance	Ratepervehicle	Rateperprofile
Vehicle type (13)	Yes if selected	Yes if selected	Yes if selected
Temperature	Yes	Yes	Yes
Road type (4)	Yes	--	--
Speed bin (16)	Yes	--	--
Type of day (2)	No	Yes	Yes
Hour of day (2`4)	No	Yes	Yes
Model year (31)	Yes if selected	Yes if selected	Yes if selected
Fuel type (3)	Yes if selected	Yes if selected	Yes if selected

3.7 Household-level GHG Emission Estimation

In our model system, once we obtain the information on households' vehicle type, quantity, usage and GHGEs rates from the discrete-continuous model, it is possible to calculate annual GHGEs for each vehicle within the households. The annual GHGEs for each vehicle can be obtained by the following formula:

$$AGHGEs\ (grams) = RERs\left(\frac{grams}{vehicle-mile}\right) * AVMT\left(\frac{miles}{year}\right) + SERs * \left(\frac{grams}{vehicle-day}\right) * 365\left(\frac{days}{year}\right)$$

Equation 3 - 42

Where AGHGEs is annual greenhouse gas emissions; RERs and SERs represent running emission rates and start/extended idle emission rates, respectively; and AVMT is annual vehicle miles traveled.

Chapter 4: Data Sources

4.1 The 2009 National Household Travel Survey (NHTS)

4.1.1 Introduction to the 2009 NHTS

The main data source we employed for both the integrated model and MOVES input data files is derived from the 2009 National Household Travel Survey (NHTS). NHTS conducted by the Federal Highway Administration (FHWA) provides comprehensive data on travel and transportation patterns of the civilian, non-institutional, non-institutionalized population in the United States. The 2009 NHTS mainly includes four different types of data files, they are household record, person record, vehicle record, and daily trip record. In this micro data set, there are totally 150,147 households, 351,275 persons, 309,163 vehicles and 1,167,321trips (*54*). Following are the general information contains by the four data files:

- Information on households (150,147)

  e.g. household members, education level, income, housing characteristics, land use

- Information on persons (351,275)

  e.g. household head or not, age, gender, work status, has license or not

- Information on each household vehicles (309,163)

  e.g. year, make, model, estimates of annual miles traveled

- Information on daily trips (1,167,321) e.g. one-way trips taken during a designated 24-hour period, including the time, the trip began and ended, trips length, composition of the travel party, transportation mode, trip purpose, typical number of transit, walk and bike trips

The NHTS is conducted as a telephone survey, using Computer-Assisted Telephone Interviewing (CATI) technology. Because respondents are questioned about what they actually do, NHTS 2009 belongs to Revealed Preferences (RP) data. To avoid sample bias, weighting factors are included for adjustment purpose.

4.1.2 Descriptive Statistics

In this part, some necessary statistical results on households' social-demographic, land use, vehicle type, ownership and usage pattern will be illustrated for both national scale and region scale. The national scale will be United Stated, and the region scale is for our target area – the D.C. Metropolitan Area. After data clean, there are 1,372 households in the D.C. Metropolitan Area, among which 107 households do not have a car (HH0), 330 households have one car (HH1), 595 households have two cars (HH2), 257 households have three cars (HH3) and 83 households have more than three cars (HH4+). Due to the small sample size of HH4+ group, we only consider households with zero, one, two and three cars, which contains 1289 households in total.

In order to make the vehicle types in all sub-models consistent, we map them from the 2009 NHTS data to MOVES source type in the table below:

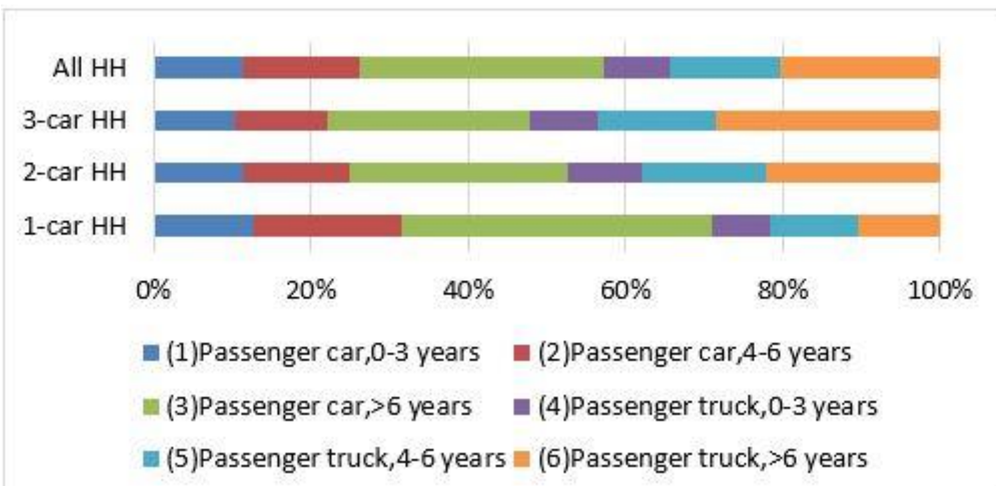
TABLE 4 - 1 Vehicle Type Mapping between NHTS and MOVES

Classification of Vehicle Type			
NHTS_ID	NHTS_TYPE	MOVES_ID	MOVES_TYPE
01	Automobile/car/station wagon	21	passenger car

02	Van (mini, cargo, passenger)	31	passenger truck
03	Sports utility vehicle	31	passenger truck
04	Pickup truck	31	passenger truck
05	Other truck	31	passenger truck
06	RV (recreational vehicle)	31	passenger truck
08	Golf cart	31	passenger truck

In the vehicle type and vintage model, we totally classify vehicles into six groups according to their sizes and vintage ranges. The figure below shows the vehicle distribution among these six groups within the Washington D.C. Metropolitan Area.

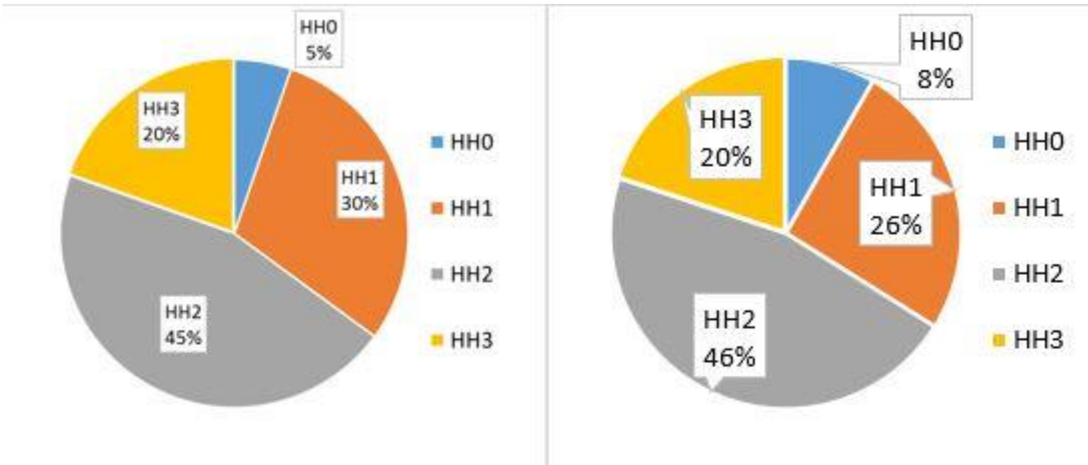
FIGURE 4 - 1 Distribution of Vehicle Type in the Washington D. C. Metropolitan Area.



A qualitative analysis of the data collected in the Washington D.C. Metropolitan Area shows that households with one vehicle prefer passenger cars (70%) to trucks (30%). For households with two or three vehicles, there is no obvious preference on passenger car or truck. Additionally, around half of vehicles in the sample are older than six years.

The distributions of car ownership in both the U.S. and the Washington D. C. Metropolitan Area are compared as follow (left diagram is for the U. S.):

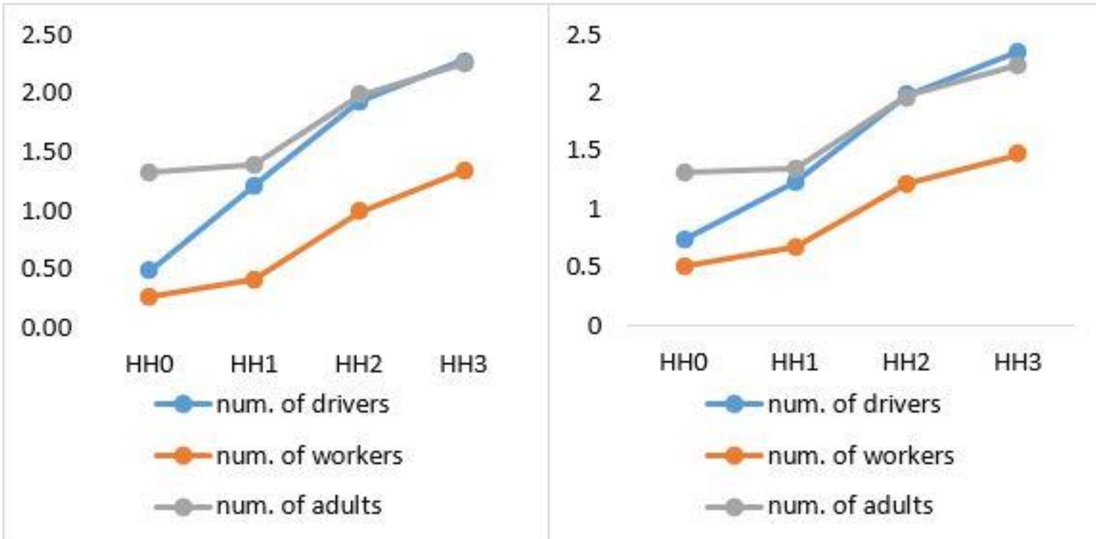
FIGURE 4 - 2 Distribution of vehicle quantity in both the U. S. and the Washington DC Area.



From the figure, we can observe that the percentage of households without cars in the D.C. Metropolitan Area is higher, while the percentage of one-car group is lower than that of the whole national scale. The percentages of households with more than one car are similar in both cases. In the Washington D.C. Metropolitan Area, almost half of the households have two vehicles and the average number of vehicles per household is 1.91; which is in line with the national average.

The relationship between households' size and the number of workers, drivers and adults can be described in the following figure. The number of adults, workers and drivers increase as households' size increases. The figure on the left is for the U. S. and the one on the right is for the D. C. Metropolitan Area.

FIGURE 4 - 3 Relationship between households' size and the number of adults, workers and drivers.

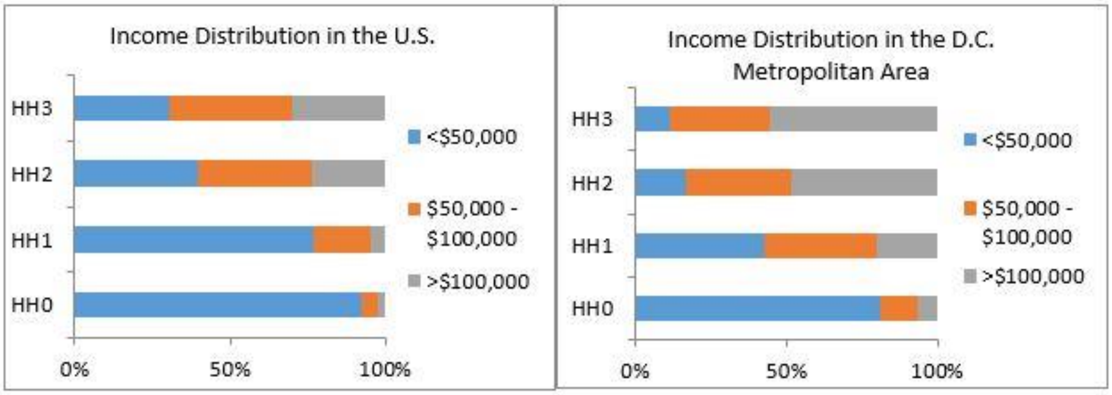


In addition, as the number of adults, workers and drivers increases with households' size, the annual VMT also increases correspondingly. The figure below describes the situation in the D. C. Metropolitan Area:

FIGURE 4 - 4 Relationship between households' size and annual VMT in the D. C. Metropolitan area.

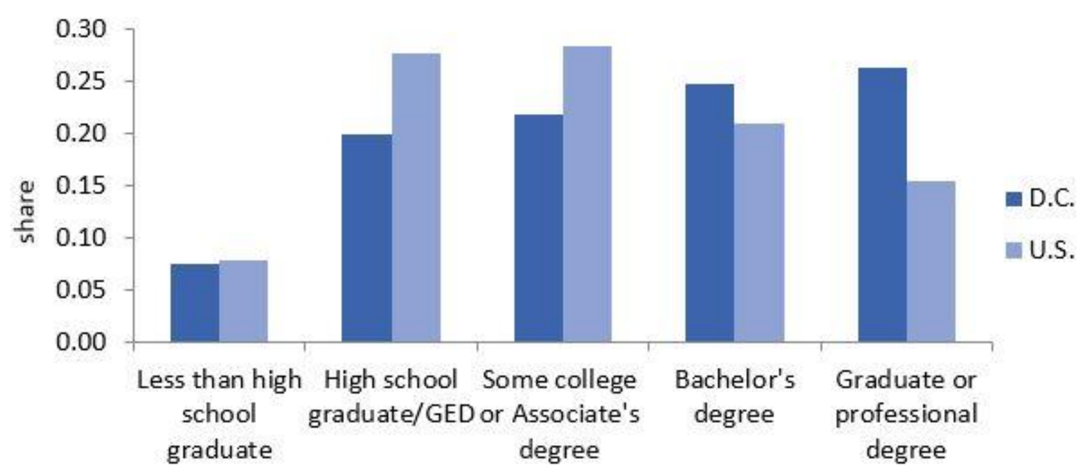
We also make comparisons of households' social-demographic variables, such as income and education level, which should be taken into consideration in our model system.

FIGURE 4 - 5 Comparison of income distribution.



From the figure, we can observe the share of high-income households is higher in the Washington D.C. Metropolitan area.

FIGURE 4 - 6 Comparison of education level distribution.



On average, the households in the D.C. Metropolitan area have higher education level than households in the whole nation. The table below show the other variables related to the integrated discrete-continuous car ownership model.

TABLE 4 - 2 Possible Variables related to the Integrated Car Ownership Model

Variables		Car Ownership				Data Statistics for D.C. Metropolitan Area		
		0 car	1 car	2 cars	3 cars	Mean	Median	S.D.
Social-demo-graphic	Owned house (1)	0.44	0.78	0.92	0.98	0.86	1	0.34
	Age of HH head	59.00	60.35	52.41	52.08	54.76	54	14.65
	HH head gender (m=1)	0.22	0.39	0.52	0.51	0.47	0	0.50
Land use	Urban area	0.93	0.85	0.78	0.61	0.76	1	0.43
	House unit/sq mile	7352	3593	1369	744	2203	750	4187
	Population/sq mile	12345	6767	3543	2215	4639	3000	6212
	Annual VMT (miles)	0	10168	12661	12285	11829	9815	8707

The 2009 NHTS data provides the Core Based Statistical Area (CBSA) code for each record. In order to obtain the county-level information, we classify all counties of Maryland state, Virginia state, West Virginia state and District of Columbia into different regions according to the CBSA code given by the 2009 NHTS. The following table shows the location distributions of 18 counties within the Washington D.C. Metropolitan area. Vehicle age distributions and average annual vehicle miles traveled (AAVMT) have been calculated for each CBSA region.

TABLE 4 - 3 Location Distributions of 18 Counties and the Rates of Vehicle per Person

State	Region	State (in D.C. Metropolitan)	CBSA	Veh/Person
Virginia (VA)	Richmond	Spotsylvania County	40060	0.97
	Arlington	Fauquier County Stafford County Loudoun County Arlington County Prince William County Fairfax County	47900	0.87
	Other	Rappahannock County Clarke County Warren County Culpeper County	Other	1.07

Maryland (MD)	Near D.C. city	Prince George's County Montgomery County	4790 0	0.80
	Other	Calvert County Charles County Frederick County	Other	0.95
West Virginia (WV)	Near D.C. city	Jefferson County	4790 0	0.62
District of Columbia	D.C. city	Washington D.C.	4790 0	0.49

TABLE 4 - 4 Vehicle Age Distribution and AAVMT in each CBSA Region

Region	Vehicle Type	Vehicle Age Distribution (share)			AAVMT
		0-3 years	4-6 years	>6 years	
Richmond (VA)	PC	19.1%	21.4%	59.5%	11139
	PT	19.0%	24.6%	56.5%	11914
Arlington (VA)	PC	21.0%	24.1%	54.9%	11451
	PT	18.4%	28.1%	53.5%	12664
Other (VA)	PC	16.1%	18.7%	65.2%	11516
	PT	14.1%	20.8%	65.1%	11587
Near D.C. city (MD)	PC	17.1%	24.6%	58.3%	11388
	PT	20.0%	28.7%	51.3%	13076
Other (MD)	PC	9.8%	23.5%	66.7%	12279
	PT	24.6%	23.1%	52.3%	11313
Near D.C. city (WV)	PC	21.1%	16.6%	62.3%	8901
	PT	19.0%	15.2%	65.8%	13158
D.C. city	PC	19.0%	19.6%	61.4%	7794
	PT	21.8%	21.8%	56.4%	10723

The rates of vehicle per person, vehicle age distribution and average annual VMT are calculated for the preparation of MOVES input data files, where “PC” stands for passenger car, and “PT” represents passenger truck.

4.2 The Consumer Reports

The *Consumer Reports* contains information of vehicle characteristics within the past ten years. The data of three tested vehicle models up to four model years have been collected. The tested models are 2003 SR5 4-door SUV 4WD, 4.0-liter V6, and Toyota 4Runner. Specifically, data of vehicle characteristics contains information on vehicle price, seating space (front, rear, third), engine size, transmission (manual or automatic), acceleration (0 to 30 mph; 0 to 60 mph; 45 to 60 mph, sec), quarter-mile, emergency handling, braking distance (from 60 mph dry; wet), comfort or convenience, ride, noise, driving position, seat comfort, shoulder room, leg room, head room, controls and display, interior fit and finish, trunk/cargo area, luggage/cargo capacity, climate system, fuel economy, cruising range, fuel capacity, fuel type, safety, specifications, length, width, height, turning circle, curb weight maximum load, and typical towing capacity (*55*). The data of vehicle characteristics generally serve for the vehicle type and vintage sub-model.

4.3 The American Fact Finder

The *American Fact Finder* provides access to data about the United States, Puerto Rico and the Island Areas. The Census Bureau conducts nearly one hundred surveys and censuses every year. Data from the following surveys and censuses are available in the *American Fact Finder*:

- **American Community Survey (ACS):** A nationwide survey designed to provide communities a fresh look at how they are changing every year. It is a critical element in the Census Bureau's decennial census program. The ACS collects information such as age, race, income, commute time to work, home value, veteran status, and other important data.
- **American Housing Survey (AHS):** A longitudinal housing unit survey conducted biennially in odd-numbered years. It provides current information on a wide range of housing subjects, including size and composition of the nation's housing inventory, vacancies, physical condition of housing units, characteristics

of occupants, indicators of housing and neighborhood quality, mortgages and other housing costs, persons eligible for and beneficiaries of assisted housing, home values, and characteristics of recent movers.

- **Annual Economic Surveys (AES):** The Census Bureau conducts more than 100 economic surveys covering annual, quarterly, and monthly time periods for various sectors of the economy. The survey data drive from three sub-survey data, they are Annual Survey of Manufactures (ASM), County Business Patterns (CBP) and ZIP Code Business Patterns (ZBP), and Non-employer Statistics (NES) Data Sets.
- **Annual Surveys of Governments:** They provide relevant, comprehensive, uniform, and quality statistics on the characteristics and key economic activities of our nation's nearly 90,000 state and local governments. The surveys provide detailed information about these governments' structure, organization, function, finances, and employment.
- **Census of Governments:** It provides periodic and comprehensive statistics about the organization, employment, and finances of all state and local governments.
- **Commodity Flow Survey:** It produces data on the movement of goods originating from the United States. It provides information on commodities shipped, their value, weight and mode of transportation, as well as the origin and destination of shipments from establishments in these industry sectors: manufacturing, mining, wholesale, and select retail and services establishments.
- **Decennial Census:** It provides age, sex, race, housing units and more for the United States, Puerto Rico, and the Island Areas every ten years.

- **Decennial Census of the Island Areas:** It provides demographic, social, economic, and housing characteristics for the Island Areas every ten years.
- **Economic Census:** It profiles the U.S. economy every 5 years, from the national to the local level and by detailed industry and business classification.
- **Economic Census of the Island Areas:** It profiles the economies of American Samoa, the Commonwealth of the Northern Mariana Islands, Guam, Puerto Rico, and the U.S. Virgin Islands every 5 years, down to the local level by detailed industry and business classification.
- **Survey of Business Owners:** It presents statistics every 5 years at the national to local area level by industry and by gender, ethnicity, race, and veteran status of the business owner.
- **Equal Employment Opportunity (EEO) Tabulation:** It publishes estimates from the American Community Survey of the race, ethnicity, and sex composition of the workforce by occupation and geography.
- **Population Estimates Program:** It publishes estimated population totals for the previous year for cities and towns, metropolitan areas, counties, and states.
- **Puerto Rico Community Survey:** An equivalent source of the American Community Survey for Puerto Rico.

Given the number of vehicles per person for each county, the vehicle share of each county can be obtained by knowing the residential population. More specifically, the vehicle share of county i in state A can be calculated as follow:

$$VS_i = \frac{RP_i * ACO_i}{\sum_{j=1}^{n} RP_j * ACO_j} \quad , \quad n = num.of\ counties\ within\ state\ A$$

Equation 4 - 1

Where $VS_i = vehicle\ share\ of\ county\ i;$

$RP_i = residential\ population\ of\ county\ i;$

$ACO_i = average\ car\ ownership\ in\ county\ i;$

n is the total number of counties within state A;

A includes Maryland, Virginia, West Virginia and District of Columbia.

It is obvious that the sum of vehicle shares of every county i within one state A is equal to 1, which can be illustrated as follows:

$$\sum_{i=1}^{n} VS_i = 1, \qquad n = num.of\ counties\ within\ state\ A$$

Equation 4 - 2

The residential population of all counties in states of Maryland, Virginia, West Virginia and District of Columbia derived from the American Community Survey (ACS) are employed for the calculation. The table below mainly provides the residential population with increasing order for the 18 counties within the Washington D.C. Metropolitan area.

TABLE 4 - 5 Residential Population over 18 Counties within the D.C. Metropolitan Area

State	Geographic area	Population
VA	Rappahannock County,VA	6983
VA	Clarke County,VA	12652
VA	Warren County,VA	31584
VA	Culpeper County,VA	34262
WV	Jefferson County,WV	42190

VA	Fauquier County,VA	55139
MD	Calvert County,MD	88737
VA	Spotsylvania County,VA	90395
VA	Stafford County,VA	92446
MD	Charles County,MD	146551
VA	Loudoun County,VA	169599
VA	Arlington County,VA	189453
MD	Frederick County,MD	233385
VA	Prince William County,VA	280813
D.C.	Washington D.C.	601723
MD	Prince George's County,MD	863420
VA	Fairfax County,VA	969749
MD	Montgomery County,MD	971777

4. 4 The 2009 State Motor Vehicle Registrations (SMVR)

The 2009 SMVR data, collected by Federal Highway Administration (FHWA) in January 2011, provides the number of Federal, state, county, and municipal vehicles, not including vehicles owned by the military services. The numbers of private and commercial buses given are estimated by FHWA of the numbers in operation, rather than the registration counts of the States. For most states the data provided are for 2009. However, table displays 2008 private and commercial and state, county and municipal vehicles for Indiana and Texas and 2007 data for Puerto Rico. The vehicle population data for Maryland state, Virginia state, West Virginia state and District of Columbia in our research are derived from Table MV-1 of the 2009 SMVR. For additional details of publicly owned vehicles and of trucks, buses, and trailers registered, see tables MV-7, 9, 10, and 11, respectively.

TABLE 4 - 6 Numbers of Passenger Cars and Trucks in each State / City

State (City)	Private Car	Private Truck
Distr. Of Columbia	162,148	41,220

Maryland	2,583,261	1,849,201
Virginia	3,700,232	2,518,709
West Virginia	686,961	683,746

We assume both the share of passenger car and passenger truck of county i within state A are equal to the vehicle share of county i within state A. Therefore, the number of passenger cars and passenger trucks in county i can be calculated as follow:

$$NV_i = TNV_A * VS_i$$

Equation 4 - 3

Where NV_i stands for the number of vehicles in county i; TNV_A represents the total number of vehicles in state A; and VS_i is the vehicle share of county i.

TABLE 4 - 7 Calculated Num. of Vehicles in Each County within the D.C. Metropolitan Area

Geographic Area in D.C. Metropolitan Area		Private Car	Private truck
Washington D.C.	Distr. Of Columbia	162148	41220
Maryland	Calvert County	44688	31989
	Charles County	73802	52831
	Frederick County	117532	84134
	Montgomery County	412112	295006
	Prince George's County	366160	262112
Virginia	Arlington County	90014	61271
	Clarke County	7393	5032
	Culpeper County	20021	13628
	Fairfax County	460752	313629
	Fauquier County	26198	17833
	Loudoun County	80581	54850
	Prince William County	133421	90818
	Rappahannock County	4081	2778
	Spotsylvania County	47886	32595
	Stafford County	43923	29898
	Warren County	18456	12563
West Virginia	Jefferson County	11182	11130

4.5 MOVES Input Database

This section covers how to develop a County Scale RunSpec for on-road sources using the County Data Manager. County Scale is required for State Implementation Plan (SIP) and Conformity analyses. County specific data must be entered when the County Scale is selected. It is important to note that local data should be used for inputs and default data is very limited. The entire RunSpec has to be set up first before the county inputs are added. This enables the County Data Manager (CDM) to filter the default database for relevant information.

First, we take Montgomery County in winter period as an example scenario to show the way to create a RunSpec for obtaining emission rates. In a RunSpec, attributes such as Description, Scale, Time Spans, Geographic Bounds, Vehicles/Equipment, Road Type, Pollutants and Processes, Manage Input Data Sets, Strategies, Output, and Advanced Performance Features should be pre-defined. The following table shows the decisions we make and notations for each part for a county scale RunSpec.

TABLE 4 - 8 Example of County Scale RunSpec for Emission Rates

Attribute	Decision	Notation
Description	"Mont, MD", "Jan&Feb", "CH4, N2O, CO2"	-
Scale	"Onroad", "County", "Emission Rates"	MOVESScenarioID is required
Time Spans	"2009", "January&February", "select all hours"	Month is to indicate different fuel or meteorological conditions
Geographic Bounds	"Zone&Link", "MD-Mont. County", "localhost", "mont_jan_feb_in"	Only one State can be selected
Vehicles/Equipment	"Gasoline-Passenger Car",	-

	"Gasoline-Passenger Truck"	
Road Type	All five type	-
Pollutants And Processes	"Total Gaseous Hydrocarbons", "CH4", "N2O", "Total Energy Consumption", "CO2"	-
Manage Input Data Sets	-	don't need to enter data in this section
Strategies	-	-
Output	"mont_jan_feb_out", "Grams", "Joules", "Miles", "Model Year", "Source Use Type"	Different rates will be estimated based on select attributes here
Advanced Performance Features	-	

After properly defining a RunSpec, we can now input required data files under County Data Manager (CDM). All data, including default data, must be imported back into the CDM from Excel for each required tab. Imported data are read from an Excel worksheet that has been properly formatted according to the format of MOVES default data. The table below presents the names and description of all MOVES input data files.

TABLE 4 - 9 Description of MOVES Input Data Files

Table Name	Table Description
Source Type Population	The number of vehicles of each source type in the country being modeled
Vehicle Type VMT	The total annual VMT by HPMS vehicle type. It also includes month, day, and hour VMT fractions
I/M Programs	Frequency of maintenance and repair
Fuel	Market share and composition of fuel blends and fractions of vehicles using each fuel type. Defaults are available by county
Meteorology Data	Temperature and humidity inputs. Meteorology data should be entered for every month and hour selected in the RunSpec
Ramp Fraction	Information about the fraction of freeway VHT occurring on ramps
Road Type Distribution	Information on the fraction of source type VMT on different road types
Age Distribution	Age fractions of fleet by age and source type. Age distribution is entered according to MOVES source types and calendar year and covers new to 30+ year old vehicles

Average Speed Distribution	Speed distribution by road type, hour, and source (vehicle) type. MOVES has 16 speed bins ranging from 2.5 to 75+ mph. Average Speed Distribution is in terms of time, not distance (i.e. fraction of VHT, not VMT, for each speed bin)
Hotelling	Total number of hours spent by truck drivers in their trucks during mandated rest periods between trips during long haul operations. This tab inputs total hotelling hours and the operating distribution for vehicles during hotelling hours. Time can be divided between extended idling and auxiliary power unit (APU) operation and other operating modes

To estimate the average GHGEs rates for the Washington D.C. Metropolitan Area, the specific data files required in our situation, together with their data source, are listed in the following table.

TABLE 4 - 10 MOVES Input Data Files for Each County in the D.C. Metropolitan Area

Input	Description	Data Source
I/M Programs	Maintenance and repair pattern	MOVES default
Source Type Population	Population for each vehicle type	NHTS 2009, American Facts Finder, The State Motor Vehicle Registrations (SMVR) 2009
Vehicle Type VMT	Total VMT for each vehicle type	NHTS 2009, The State Motor Vehicle Registrations (SMVR) 2009, MOVES AAVMT Calculator
Age Distribution	The percentage of vehicles in each age range	NHTS 2009
Average Speed Distribution	The percentage of miles in each speed bin	MOVES documentations MOVES default
Fuel	Fuel supply and formulation of target region	MOVES default
Meteorology Data	Daily temperature and humility in target month	MOVES default + modification for emission rates
Road Type Distribution	The percentage of roads in each road type	Assumption
Ramp	The slope of roads	MOVES default

Chapter 5: Estimation Results for the Model System

5.1 Results for Vehicle Type and Vintage Sub-Model

A multinomial logit model has been employed to estimate vehicle type and vintage conditional on vehicle quantities holding by households. In other words, we use three separate multinomial logit model to estimate vehicle type and vintage for one-car households (HH1), two-car households (HH2) and three-car households (HH3), respectively. The sample size derived from the 2009 NHTS for HH1, HH2 and HH3 in the Washington D.C. Metropolitan Area are 330, 595 and 257, respectively.

5.1.1 Model Estimation Results

For one-car households, the model has six alternatives categorized by vehicle size and vintage, which includes the full choice set. For two-car households, according to IIA (independence of irrelevant alternatives) property, a subset of ten alternatives (including the one chosen by the household) has been randomly chosen from the full choice set of (6*6=) 36 alternatives. Similarly, a subset of twenty alternatives has been randomly chosen from the full set of (6*6*6=) 216 alternatives for three-car households. For comparison purpose, we consider the same variables for three models, the variables are shoulder room (inch), luggage space (cubic feet), number of makes and models in certain class, fuel economy (overall MPG), dummy variable of one new car (less than 3 years old) within households, and purchase price ($1000). The estimation results are given in Table 5-1.

TABLE 5 - 1 Vehicle Type and Vintage Sub-Model: Estimation Results

	One-car HH (HH1)		Two-car HH (HH2)		Three-car HH (HH3)	
Variables	coefficient	t-value	coefficient	t-value	coefficient	t-value
Sum of shoulder room	0.0044	0.3	0.0401	4.5	0.0300	2.9
Sum of luggage space	0.2997	6.4	0.0369	2.4	0.0610	3.9
Log(no. of make/model in class)	1.0390	8.2	0.8580	15.2	0.8981	12.6
Overall MPG (city & highway)	0.0492	1.6	0.0715	4.7	0.0418	2.3
D. one new car (0-3 years)	0.3646	1.8	0.3653	2.8	0.5973	3.2
Purchase price (in.<40k)	-0.1250	-5.6	-	-	-	-
Purchase price (in.=40-80k)	-0.0716	-3.6	-	-	-	-
Purchase price (in.>80k)	-0.0614	-3.0	-	-	-	-
Purchase price (in.<60k)	-	-	-0.1410	-9.3	-0.2638	-8.4
Purchase price (in.=60-100k)	-	-	-0.1067	-8.2	-0.1317	-7.4
Purchase price (in.>100k)	-	-	-0.0666	-7.0	-0.0827	-7.3
No. of observations	330		595		257	
Final Log-likelihood	-498.3		-1099.6		-534.38	
Log-likelihood at zero	-591.3		-1370.0		-769.9	
R^2	0.157		0.197		0.306	

The value of R square, between 0 and 1, generally measures the goodness of fit for the models. It can be calculated as follows:

$$L(0) = -N * \ln(J)$$

$$R^2 = 1 - \frac{L(\beta)}{L(0)}$$

Equation 5 - 1

Where N is the number of observations and J is the number of alternatives; $L(0)$ represents the log-likelihood when the coefficients equal to zero. $L(\beta)$ represents the log-likelihood after convergence.

From Table 5-1, we can observe that except for the shoulder room for one-car households, the coefficients of all other variables are significant. In addition, all coefficients have the reasonable sign. Coefficients of shoulder room and luggage space are positive, indicating households prefer vehicles with larger space.

Coefficients of the number of makes and models in certain class and vintage are positive, meaning households tend to choose the class and vintage with more makes and models. Coefficients of fuel economy are also positive, illustrating that households prefer vehicles with higher miles per gallon (MPG). Dummy of one new car within household is positive as well, describing that households prefer to hold one vehicle less than 3 years old. Last but not least, the coefficients for purchase price is negative as expected, indicating that households prefer cheaper vehicles.

5.1.2 Distribution of Logsum

The logsum has been calculated from vehicle type and vintage sub-model (see 3.2.2). Each household has four logsums for 0 car, 1 car, 2 cars and 3 cars holding cases. The logsum of holding zero-car has been set to zero as a base case. In this model system, logsum indicates the maximum expected utility from vehicle type and vintage combinations conditional on the car quantity holding by a household. The distribution of logsum is given by Table 5-2.

TABLE 5 - 2 Distribution of Logsum

Group ID	Max.	Min.	Mean	Median	S.D.
HH1	7.7041	5.3330	6.8426	6.8926	0.3839
HH2	20.0861	16.0301	18.3170	18.3664	0.7405
HH3	24.1380	16.3078	21.0881	21.6865	2.0301

5.2 Results for Integrated Vehicle Ownership and Usage Sub-Model

The integrated discrete-continuous model estimates the number of cars holding by households and their preferences in driving the primary car, the secondary car and the tertiary car within households. Specifically, the integrated model combines a multinomial probit model for households' car quantity and three regressions for annual miles traveled by the primary car, the secondary car and the tertiary car within households. The sample size for car quantity probit model is 1289 households, and the sample size for three regressions are 1182, 852 and 257, respectively. In this research, we are only interested in households living in the Washington D.C. Metropolitan Area and the data are obtained from the 2009 NHTS.

5.2.1 Model Estimation Results

For the discrete part, the car quantity sub-model contains four alternatives – 0 car, 1 car, 2 cars and 3 cars. The variables considered are mainly social-demographic and land use variables, such as households' income, number of drivers within households, gender of households' head, and residential density. For the continuous part, three VMT regressions, the dependent variables are the annual miles traveled by households' primary car, secondary car and tertiary car, respectively. The independent variables for the regressions are households' income, gender of households' head, residential density and driving cost. The estimation results for the integrated model are given by Table 5-3.

TABLE 5 - 3 Joint Discrete-Continuous Model: Estimation Results

Variable	Alternative	Coefficient	S.D.	p-value
Logsum of type / vintage	all	0.803	0.007	<0.001
Constant	1 car	-6.497	0.040	<0.001
	2 cars	-19.852	NAN	NAN
	3 cars	-24.973	0.116	<0.001
Income_low	1 car	0.106	0.029	<0.001
	2 cars	0.232	0.040	<0.001
	3 cars	0.403	0.036	<0.001
Income_mid	1 car	0.114	0.025	<0.001
	2 cars	0.266	0.015	<0.001
	3 cars	0.139	0.043	0.001
Income_high	1 car	0.006	0.018	0.744

	2 cars	0.161	0.026	<0.001
	3 cars	0.108	0.026	<0.001
Num. of drivers	1 car	1.103	0.043	<0.001
	2 cars	2.942	NAN	NAN
	3 cars	3.953	NAN	NAN
HH head gender (1 for Male)	1 car	0.759	0.054	<0.001
	2 cars	1.262	NAN	NAN
	3 cars	1.360	NAN	NAN
Res. Density / low income	1 car	-0.150	0.027	<0.001
	2 cars	-0.345	0.078	<0.001
	3 cars	-0.279	0.078	<0.001
Res. Density / mid income	1 car	-0.181	0.034	<0.001
	2 cars	-0.303	0.035	<0.001
	3 cars	-0.478	0.048	<0.001
Res. Density / high income	1 car	-0.001	0.022	0.956
	2 cars	-0.331	NAN	NAN
	3 cars	-0.630	0.055	<0.001
Constant	Regression for primary vehicle	5.014	0.123	<0.001
Income		0.050	0.007	<0.001
HH head gender		0.243	NAN	NAN
Res. density		-0.052	0.009	<0.001
Driving cost		-2.983	0.057	<0.001
Constant	Regression for secondary vehicle	5.088	NAN	NAN
Income		0.023	NAN	NAN
HH head gender		-0.117	0.044	0.008
Res. density		-0.142	0.013	<0.001
Driving cost		-2.648	0.036	<0.001
Constant	Regression for tertiary vehicle	5.190	NAN	NAN
Income		0.014	NAN	NAN
HH head gender		-0.112	0.042	0.009
Res. density		-0.139	0.013	<0.001
Driving cost		-2.651	0.029	<0.001
Log-likelihood at zero	-3815.39			
Log-likelihood at convergence	-2840.296			
Number of observations	1289			
R square	0.256			

**Note: the model use numerical computation method to obtain hessian matrix and covariance matrix, "NANs" have been produced due to small sample size and data structure; a simulation method like bootstrapping can be applied to improve the results.*

From Table 5-3, we can observe that most coefficients are significant and have the expected sign, with only a few exceptions. Positive coefficients of households' income indicate that households with higher income tend to hold more vehicles and drive more. Besides, the coefficients for households' income indicate that the number of vehicles and their usage are more sensitive to income for low-income households and households with more vehicles. The positive coefficients of number of drivers indicate households prefer to have more cars if there are more drivers within the households. The positive coefficients of households' head gender indicate male households' head are more likely to hold more cars and drive the primary vehicle more frequently.

The negative coefficients of residential density indicate that households living in areas with higher population density prefer to hold fewer cars and drive less. In other words, households living in suburban or rural areas instead of urban areas are more likely to hold more cars. The values of the coefficients indicate that the number of vehicles and their usage are more sensitive to residential density for households with more vehicles.

The negative coefficients of driving cost indicate that households tend to drive less under higher driving cost as expected. The values of coefficients indicate that the usage of primary car is more sensitive to driving cost. The driving cost is measured by dollars per mile.

The logsum represents the utility of choosing vehicle type and vintage conditional on the number of vehicles holding by households. The coefficient of logsum reflects the correlation between vehicle holding decision and vehicle type and vintage decision. As expected, the coefficient of logsum is significant, positive, and between zero and one, which makes the vehicle type sub-model and vehicle quantity sub-model consistent.

5.2.2 Matrices of Covariance in Difference

The covariance matrices of the model after taking utility difference are reported below. The dimension of the covariance matrix conditional on holding *N* cars is (*N-1+3=*) *N+2*, where minus 1 is for normalization purpose and plus 3 is the total number of regressions. Thus, households holding different number of cars have different covariance matrices.

For HH0: Covariance Matrix after Taking Utility Difference

$$\begin{pmatrix} 2.00 & 1.34 & 1.83 \\ 1.34 & 4.56 & 4.02 \\ 1.83 & 4.02 & 8.72 \end{pmatrix}$$

For HH1: Covariance Matrix after Taking Utility Difference

$$\begin{pmatrix} 2.00 & 1.34 & 1.83 & -0.48 \\ 1.34 & 4.56 & 4.02 & 0.42 \\ 1.83 & 4.02 & 8.72 & 1.30 \\ -0.48 & 0.42 & 1.30 & 1.00 \end{pmatrix}$$

For HH2: Covariance Matrix after Taking Utility Difference

$$\begin{pmatrix} 2.00 & 1.34 & 1.83 & -0.48 & 0.21 \\ 1.34 & 4.56 & 4.02 & 0.42 & -0.02 \\ 1.83 & 4.02 & 8.72 & 1.30 & 0.37 \\ -0.48 & 0.42 & 1.30 & 1.00 & 0.07 \\ 0.21 & -0.02 & 0.37 & 0.07 & 0.43 \end{pmatrix}$$

For HH3: Covariance Matrix after Taking Utility Difference

$$\begin{pmatrix} 2.00 & 1.34 & 1.83 & -0.48 & 0.21 & 0.22 \\ 1.34 & 4.56 & 4.02 & 0.42 & -0.02 & -0.03 \\ 1.83 & 4.02 & 8.72 & 1.30 & 0.37 & 0.43 \\ -0.48 & 0.42 & 1.30 & 1.00 & 0.07 & 0.07 \\ 0.21 & -0.02 & 0.37 & 0.07 & 0.43 & 0.42 \\ 0.22 & -0.03 & 0.43 & 0.07 & 0.42 & 0.42 \end{pmatrix}$$

5.3 Model Prediction and Validation

For prediction purpose, we simulate households' vehicle holding and usage decisions based on the explanatory variables of the entire sample, the estimated coefficients, and the simulated error terms with correlation. The simulated decisions for household i can be expressed as follows:

$$Y_i = X_i \widehat{\beta_i} + \widehat{\varepsilon_i}$$

Equation 5 - 2

Table 5-4 reports households' actual choices, predicted choices and their differences. The model slight under-predicts vehicle ownership and mileage traveled by the secondary and the tertiary vehicles, while over-predicts the mileage traveled by the primary vehicle. The prediction takes the average of 50 times simulated results.

TABLE 5 - 4 Joint Discrete-Continuous Model: Prediction

		Actual	Forecast	Difference
Car Ownership	0-car household	8.3%	11.6%	3.3%
	1-car household	25.6%	23.3%	-2.3%
	2-car household	46.2%	45.2%	-1.0%
	3-car household	19.9%	19.8%	-0.1%
	Average car ownership	1.78	1.73	-2.5%
AAVMT (average annual vehicle miles traveled)	Primary car mileage	11883.1	12441.1	4.7%
	Secondary car mileage	12148.6	11794.4	-2.9%
	Tertiary car mileage	11546.6	9998.6	-13.4%
	Average mileage	11944.1	11926.6	-0.1%

For validation purpose, the entire sample size has been divided into two parts – part 1 contains 80% of the sample population and part 2 contains the rest 20% of the sample population. We re-estimate the model on 80% of the households (part 1) and apply the estimated coefficients on the rest 20% of the households (part 2). We report the actual vehicle ownership and usage for the 20% households (part 2) of the sample population, the predicted vehicle ownership and usage, and their differences in Table 5-5. The results show that the model slightly under-predicts vehicle ownership and the average annual vehicle miles traveled (VMT).

TABLE 5 - 5 Joint Discrete-Continuous Model: Validation

		Actual	Forecast	Difference
Car Ownership	0-car household	10.9%	13.2%	2.3%
	1-car household	22.6%	22.6%	0.0%
	2-car household	45.5%	44.7%	-0.8%
	3-car household	21.1%	19.5%	-1.5%
	Average car ownership	1.77	1.71	-3.4%
AAVMT (average annual vehicle miles traveled)	Primary car mileage	11753.3	11960.7	1.8%
	Secondary car mileage	12790.7	12310.5	-3.8%
	Tertiary car mileage	12095.2	10372.6	-14.2%
	Average mileage	12159.7	11906.6	-2.1%

5.4 Model Application

Sensitivity analysis has been conducted to test different scenarios of taxation policies. We are mainly interested in three vehicle-related taxes – purchase tax, ownership tax and fuel tax during vehicle purchase, holding and usage processes, respectively. Therefore, the impacts on vehicle holding and usage decisions from the changes of purchase price, income and fuel cost have been predicted in Table 5-5. Three scenarios have been tested for the interested variables, which are listed below:

- Purchase price: increases 10%, increases 20%, increases 40%
- Household income: decreases 2.2%, decreases 4.4%, decreases 8.7%
- Fuel cost: increases 5%, increases 10%, increases 20%

From Table 5-6, we observe that vehicle purchase price has the greatest impact on households' vehicle holding. For instance, the average vehicle quantity decreases 8.5% when vehicle purchase price has been increased by 40%. In contrast, household income and fuel cost have slight influences on vehicle holding decisions. For example, increasing the fuel cost by 20%, the average vehicle quantity only decreases 0.36%.

TABLE 5 - 6 Application Results for Car Ownership

	0-car hh	1-car hh	2-car hh	3-car hh	Ave. car num.
Predicted	11.75%	23.61%	44.99%	19.65%	1.73
Fuel cost +5%	11.62%	23.52%	44.98%	19.88%	1.73 -0.01%
Fuel cost +10%	11.74%	23.37%	45.22%	19.67%	1.73 -0.16%
Fuel cost +20%	11.78%	23.51%	45.25%	19.46%	1.73 -0.36%
Income -2.2%	11.83%	23.65%	44.64%	19.88%	1.73 -0.01%
Income -4.4%	12.16%	23.93%	43.87%	20.04%	1.72 -0.44%
Income -8.7%	12.34%	24.73%	43.02%	19.91%	1.71 -1.19%
Purchase price +10%	12.27%	24.52%	45.82%	17.39%	1.68 -2.51%
Purchase price +20%	12.95%	25.00%	45.51%	16.55%	1.66 -4.16%
Purchase price +40%	14.39%	26.47%	44.88%	14.26%	1.59 -8.50%

The same policy scenarios have been applied to vehicle mileage regressions. Table 5-7 reports the prediction which is the average for 50 simulated results. Fuel cost has the greatest impact on households' vehicle usage. For instance, the average VMT of the primary vehicle will decrease 18.3% when fuel cost has been increased by 20%. In contrast, vehicle purchase price has slight influence on vehicle usage decisions. For example, increasing the vehicle purchase price by 20%, the average VMT of the primary vehicle only decreases 0.4%. Household income has higher impact on the average VMT of the primary vehicle than the secondary and the tertiary vehicles. For example, the average VMT of the primary vehicle, the secondary vehicle, and the tertiary vehicle will decrease 5.47%, 2.18%, and 1.98% respectively when household income decreases by 8.7%.

TABLE 5 - 7 Application Results for Annual VMT

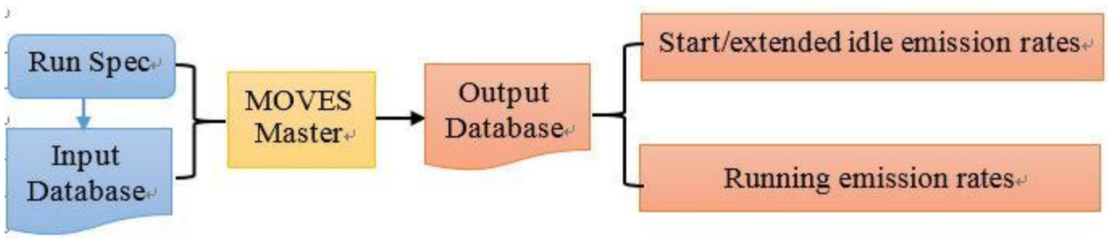
	Primary vehicle mileage	Secondary vehicle mileage	Tertiary vehicle mileage
Predicted	12456.6	11755.8	9833.8

Fuel cost +5%	11869.9	-4.71%	11318.5	-3.72%	9504.4	-3.35%
Fuel cost +10%	11321.7	-9.11%	10769.0	-8.39%	8836.8	-10.14%
Fuel cost +20%	10177.1	-18.30%	9738.3	-17.16%	7701.8	-21.68%
Income -2.2%	12297.2	-1.30%	11680.9	-0.64%	9859.4	0.26%
Income -4.4%	12085.0	-3.07%	11687.8	-0.58%	9849.2	0.16%
Income -8.7%	11810.2	-5.47%	11505.3	-2.18%	9642.8	-1.98%
Purchase price +10%	12427.8	-0.23%	11781.0	0.21%	9859.4	0.26%
Purchase price +20%	12406.6	-0.40%	11740.0	-0.13%	9817.0	-0.17%
Purchase price +40%	12450.8	-0.05%	11736.9	-0.16%	9802.6	-0.32%

5.5 Results for Vehicle GHGEs Rates Sub-Model

MOVES2014 is employed to estimate the GHGEs rates for the Washington D.C. Metropolitan Area. The simplified estimation process of households' vehicle GHGEs rates can be illustrated in Figure 5-1.

FIGURE 5 - 1 Flowchart of Emission Rates Estimation in MOVES



We choose county level instead of country level or project level, because it is suitable for our target area containing 18 counties over four states. Table 5-8 reports the names of 18 counties, their corresponding states, residential population, vehicle population, and average vehicle per person. The counties are listed in the increasing order according to their residential population.

TABLE 5 - 8 Vehicle Population and Average Vehicle Rate over 18 Counties

State	Geographic area	Population	Num. of Veh	#Veh/Per
VA	Rappahannock County,VA	6983	6858	1.07
VA	Clarke County,VA	12652	12426	1.07
VA	Warren County,VA	31584	31019	1.07
VA	Culpeper County,VA	34262	33649	1.07
WV	Jefferson County,WV	42190	22311	0.62

VA	Fauquier County,VA	55139	44031	0.87
MD	Calvert County,MD	88737	76677	0.95
VA	Spotsylvania County,VA	90395	80481	0.97
VA	Stafford County,VA	92446	73822	0.87
MD	Charles County,MD	146551	126633	0.95
VA	Loudoun County,VA	169599	135431	0.87
VA	Arlington County,VA	189453	151285	0.87
MD	Frederick County,MD	233385	201666	0.95
VA	Prince William County,VA	280813	224240	0.87
D.C.	Washington D.C.	601723	203368	0.49
MD	Prince George's County,MD	863420	628272	0.80
VA	Fairfax County,VA	969749	774381	0.87
MD	Montgomery County,MD	971777	707118	0.80

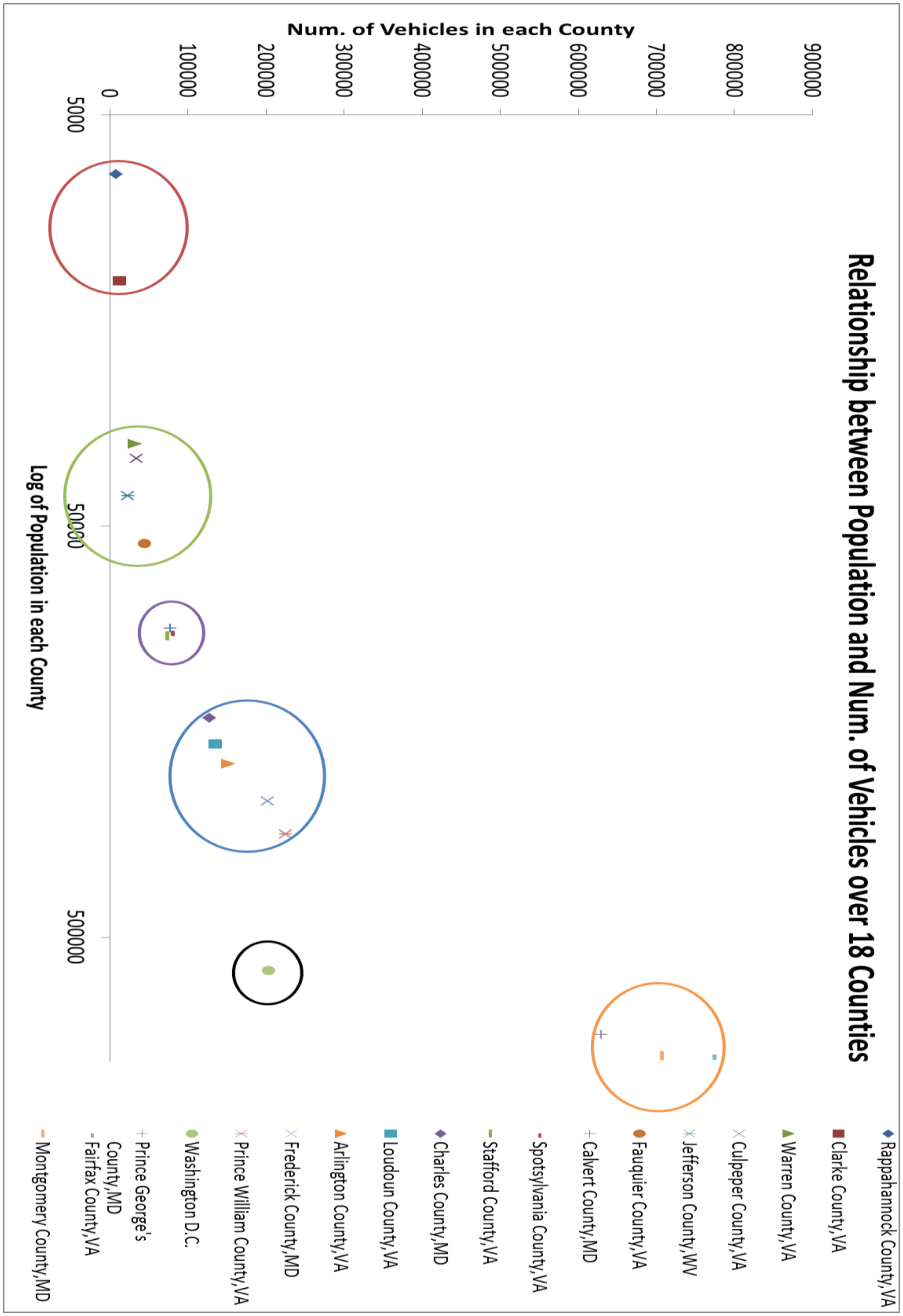
Table 5-9 reports the total annual miles traveled by all vehicles within each county. The data, serving as input data of MOVES2014, is calculated from the 2009 NHTS.

TABLE 5 - 9 Vehicle Population and Average Annual Mileage over 18 Counties

State	County	Total num. of vehicles	Tot. annual miles for county (1000 Kmiles)
VA	Rappahannock County	6858	158
VA	Clarke County	12426	287
WV	Jefferson County	22311	492
VA	Warren County	31019	716
VA	Culpeper County	33649	777
VA	Fauquier County	44031	1060
VA	Stafford County	73822	1778
MD	Calvert County	76677	1809
VA	Spotsylvania County	80481	1855
MD	Charles County	126633	2987
VA	Loudoun County	135431	3261
VA	Arlington County	151285	3643
MD	Frederick County	201666	4758
D.C.	Distr. Of Columbia	203368	3841
VA	Prince William County	224240	5400
MD	Prince George's County	628272	15370
MD	Montgomery County	707118	17299
VA	Fairfax County	774381	18647

To avoid estimating GHGEs rates for all 18 counties within the Washington D.C. Metropolitan Area, a cluster analysis is used to group the 18 counties by their vehicle population and total VMT, which are important factors for determining GHGEs rates. Figure 5-2 reports the clustering analysis results by vehicle population over 18 counties.

FIGURE 5 - 2 Clustering analysis by vehicle population over 18 counties.



The counties are categorized into six groups based on their relationship between residential population and vehicle population. From Table 5-10, the first group with the smallest residential population and vehicle population contains Rappahannock County and Clarke County; and the last group with the largest residential population and vehicle population contains Prince George's County, Fairfax County and Montgomery County. For each group, we choose one as a representative county according to available data. We assume the GHGEs rates for each group can be represented by the GHGEs rates estimated from the representative county. In Table 5-10, the vehicle shares for the six groups are 0.5%, 3.7%, 6.5%, 23.8%, 5.8% and 59.7%, respectively.

TABLE 5 - 10 County Classification by Residential Population and Num. of Vehicles

Group ID	Counties	Representative County	Share of the group
1	Rappahannock County,VA	Rappahannock, VA	0.5%
	Clarke County,VA		
2	Warren County,VA	Jefferson County, WV	3.7%
	Culpeper County,VA		
	Jefferson County,WV		
	Fauquier County,VA		
3	Calvert County,MD	Calvert County, MD	6.5%
	Spotsylvania County,VA		
	Stafford County,VA		
4	Charles County,MD	Arlington County,VA	23.8%
	Loudoun County,VA		
	Arlington County,VA		
	Frederick County,MD		
	Prince William County,VA		
5	Washington D.C.	Washington D.C.	5.8%
6	Prince George's County,MD	Montgomery County, MD	59.7%
	Fairfax County,VA		
	Montgomery County,MD		

FIGURE 5 - 3 Clustering analysis by vehicle population over 18 counties.

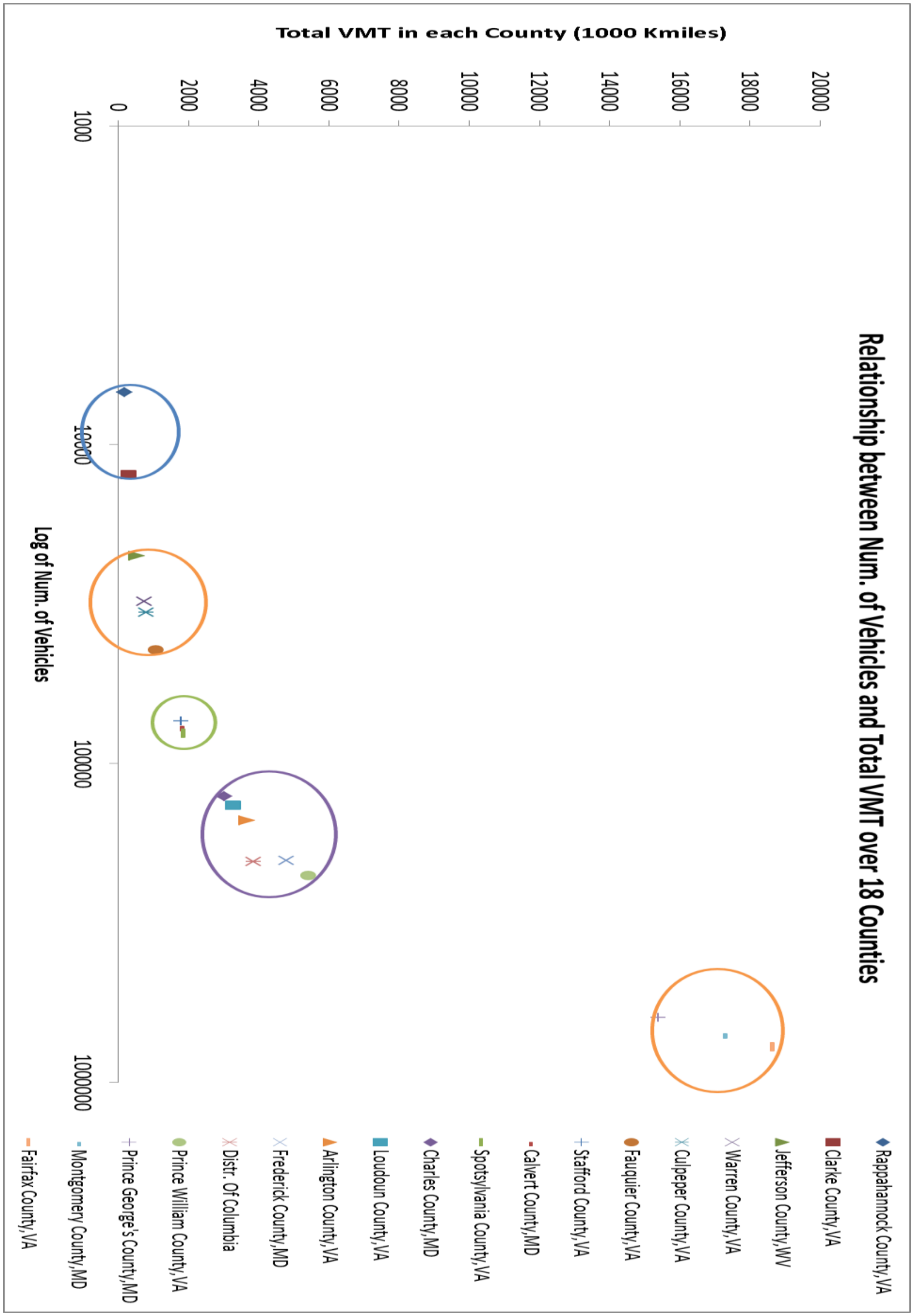


Figure 5-3 above reports the clustering analysis results by the total VMT over 18 counties. The counties are categorized into five groups based on the relationship between their vehicle population and total VMT of the counties. The only difference compared to Figure 5-2 is that the city of Washington D.C. has been merged into group 4. Based on available data, the representative counties for five groups are Rappahannock County, Jefferson County, Calvert County, Arlington County and Montgomery County. The vehicle shares for the five groups are 0.5%, 3.7%, 6.5%, 29.6% and 59.7%, respectively.

For the reasons that (a) vehicle population increases monotonically with increasing residential population, and (b) vehicle population and total VMT are the most important factors to determine GHGEs rates, we choose to categorize 18 counties into five groups in Table 5-11.

TABLE 5 - 11 County Classification based on Relationship between Total VMT and Num. of Vehicles

Group ID	Counties	Representative County	Vehicle share of the group
1	Rappahannock County,VA	Rappahannock, VA	0.5%
	Clarke County,VA		
2	Warren County,VA	Jefferson County, WV	3.7%
	Culpeper County,VA		
	Jefferson County,WV		
	Fauquier County,VA		
3	Calvert County,MD	Calvert County, MD	6.5%
	Spotsylvania County,VA		
	Stafford County,VA		
4	Charles County,MD	Arlington County,VA	29.6%
	Loudoun County,VA		
	Arlington County,VA		
	Frederick County,MD		
	Prince William County,VA		
	Washington D.C.		

5	Prince George's County,MD Fairfax County,VA Montgomery County,MD	Montgomery County, MD	59.7%

Based on vehicle shares and emission rates look-up tables of the five groups, a weighted average of GHGEs rates can be calculated for the entire Washington D.C. Metropolitan Area. As expected, the groups with small vehicle shares will have very slight impact on calculating the average GHGEs rates. Therefore, the impact from the first two groups has been ignored. The emission rates look-up tables for Calvert County, Arlington County and Montgomery County have been estimated as follows.

Several assumptions are made: (a) the annual GHGEs rates are the average emission rates of typical summer month (July and August) and typical winter month (January and February); (b) the vehicle age is an integer, defined as the difference between the current year (2009 for NHTS data) and the vehicle model year; (c) we only consider gasoline vehicles and ignore electricity and hybrid ones; (d) The GHGEs rates of the Washington D.C. Metropolitan Area are the average GHGEs rates of Calvert County, Arlington County and Montgomery County determined by the clustering analysis of vehicle population and total VMT; (e) we only consider weekdays and assume 30 weekdays instead of 22 weekdays and 4 weekends in a month; (f) assume the number of vehicles traveling in a county equals to the number of registered vehicles of that county and (g) the share of hydrofluorocarbons (HFCs) is assumed to be 3% according to the EPA (*38*).

For each county, there are two estimated GHGEs rates look-up tables. One describes start and extended idle emission rates (grams per vehicle per day) and the other describes running emission rates (grams per vehicle per mile). Table 5-11 and

5-12 are for Montgomery County, Table 5-13 and 5-14 are for Arlington County, Table 5-15 and 5-16 are for Calvert County. For calculating the average vehicle running emission rates, the speed distribution by road types extracted from the EPA (*56*) is a significant factor.

FIGURE 5 - 4 Example speed distribution by road type (56).

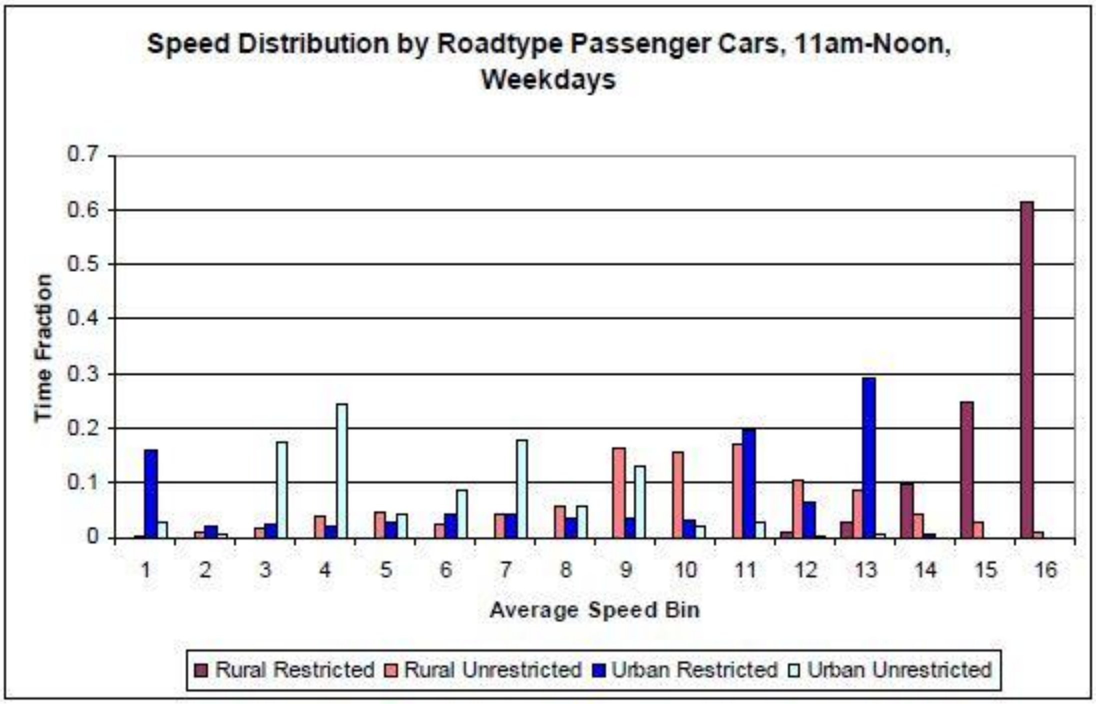


TABLE 5 - 12 Montgomery County: Start and Extended Idle Emission Rates

Average	Passenger Car				Passenger Truck			
age	CH4	N2O	CO2	CO2E	CH4	N2O	CO2	CO2E
0-3 year	0.291	0.214	615.730	688.023	0.412	0.290	800.010	898.482
4-6 year	0.343	0.214	615.732	689.133	0.542	0.294	798.096	900.732
>6 year	0.144	0.214	615.730	684.937	0.313	0.288	797.998	893.719

TABLE 5 - 13 Montgomery County: Running Emission Rates

Average	Passenger Car				Passenger Truck			
age	CH4	N2O	CO2	CO2E	CH4	N2O	CO2	CO2E
0-3 year	0.004	0.008	398.256	400.794	0.004	0.020	576.368	582.496
4-6 year	0.004	0.008	398.363	400.909	0.009	0.021	576.572	583.113
>6 year	0.004	0.008	398.469	401.023	0.008	0.020	577.806	584.116

TABLE 5 - 14 Arlington County: Start and Extended Idle Emission Rates

Average	Passenger Car				Passenger Truck			
age	CH4	N2O	CO2	CO2E	CH4	N2O	CO2	CO2E
0-3 year	0.267	0.214	591.507	663.301	0.378	0.290	768.029	865.789
4-6 year	0.321	0.214	591.506	664.431	0.510	0.294	766.194	868.160
>6 year	0.139	0.214	591.507	660.617	0.305	0.288	766.098	861.667

TABLE 5 - 15 Arlington County: Running Emission Rates

Average	Passenger Car				Passenger Truck			
age	CH4	N2O	CO2	CO2E	CH4	N2O	CO2	CO2E
0-3 year	0.004	0.008	400.287	402.825	0.004	0.020	579.175	585.303
4-6 year	0.004	0.008	400.415	402.960	0.009	0.021	579.408	585.949
>6 year	0.004	0.008	400.542	403.093	0.008	0.020	580.676	586.981

TABLE 5 - 16 Calvert County: Start and Extended Idle Emission Rates

Average	Passenger Car				Passenger Truck			
age	CH4	N2O	CO2	CO2E	CH4	N2O	CO2	CO2E
0-3 year	0.258	0.214	583.519	655.123	0.365	0.290	757.973	855.462
4-6 year	0.307	0.214	583.521	656.162	0.490	0.294	756.159	857.704
>6 year	0.133	0.214	583.521	652.493	0.292	0.288	756.063	851.344

TABLE 5 - 17 Calvert County: Running Emission Rates

Average	Passenger Car				Passenger Truck			
age	CH4	N2O	CO2	CO2E	CH4	N2O	CO2	CO2E
0-3 year	0.004	0.008	400.606	403.145	0.004	0.020	579.616	585.744
4-6 year	0.004	0.008	400.737	403.284	0.009	0.021	579.854	586.395
>6 year	0.004	0.008	400.868	403.422	0.008	0.020	581.126	587.438

Comparing the running emission rates look-up tables between different counties, we observe that the running emission rates have insignificant variations for the same vehicle size. More specifically, the running emission rates of passenger cars are around 540 grams per mile and the running emission rates of passenger trucks are around 760 grams per mile, irrespective of county and model year. The look-up tables indicate that vehicle running emission rates are not sensitive to vehicle model years and geographic areas.

Comparing the start and extended idle emission rates look-up tables, we observe that the start and extended idle emission rates have obvious variations for the same vehicle size over geographic areas. The start and extended emission rates are higher in counties with higher vehicle population. In other words, the start and extended idle emission rates decrease monotonically as the vehicle population decreases. For example, Figure 5-5 compares the start and extended idle emission rates among Montgomery County with high vehicle population, Arlington County with medium vehicle population, and Calvert County with low vehicle population.

FIGURE 5 - 5 Comparison of start and extended idle emission rates over three counties.

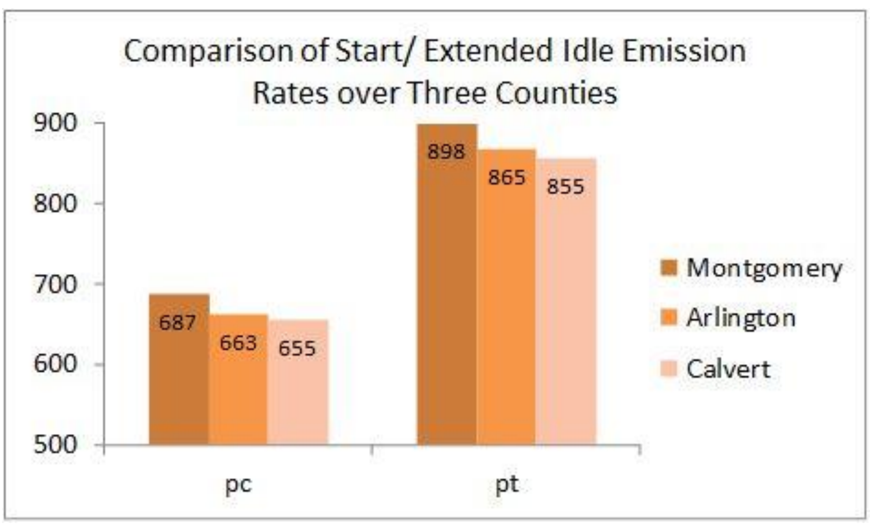
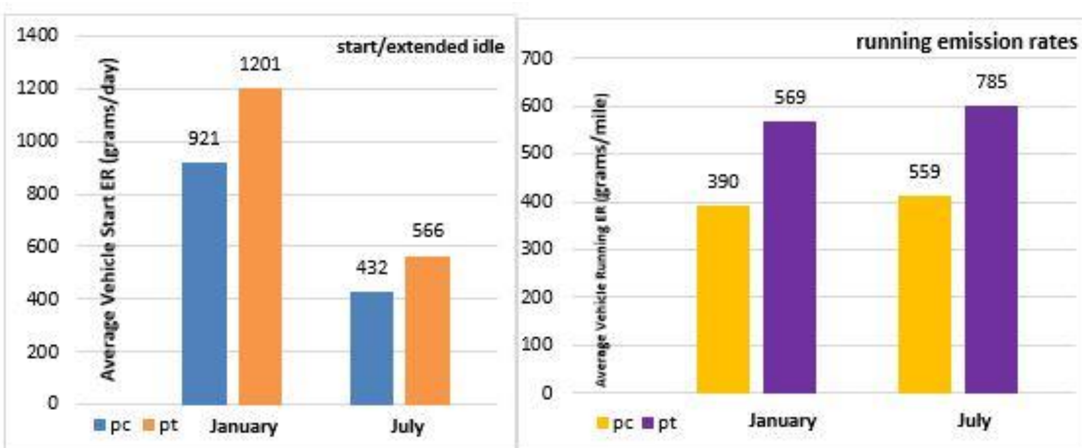


Figure 5-6 compares both start/extended idle (left) and running emission rates (right) between the typical summer month (July) and the typical winter month (January) for the Washington D.C. Metropolitan Area. For comparison purpose, the emission rates of all pollutants have been transformed into CO_2 equivalent (CO_2E). "pc" represents passenger car and "pt" represents passenger truck.

FIGURE 5 - 6 Comparison of vehicle start/extended idle and running emission rates between typical summer and winter months.



From Figure 5-6, it is obvious that passenger trucks generate higher GHGEs rates than passenger cars during both start/extended idle and running processes. Moreover, the start/extended idle emission rates in January are more than twice of those in July, which is reasonable due to longer start time and more fuel consumptions in winter. In the running process, the emission rates in January are slightly lower than those in July mainly because of incomplete combustion under low temperatures (*57, 58*). Table 5-17 and 5-18 specifically show both start/extended idle and running emission rates in the Washington D.C. Metropolitan Area. It should be noted that the results indicate a lack of vehicle age sensitivity when estimating GHGEs rates.

There are two steps to calculate the weighted average of emission rates: (a) merge the vehicle shares of the first two groups into group 3, thus, the vehicle share of group 3 is (0.5% + 3.7% + 6.5% =) 10.7%, and (b) calculate the weighted average emission rates over the three counties according to their vehicle shares – 10.7%, 29.6% and 59.7%. Table 5-17 reports the weighted average start and extended idle emission rates (grams per vehicle per day) of the Washington D.C. Metropolitan Area. Table 5-18 reports the weighted average running emission rates (grams per vehicle per miles) of the Washington D.C. Metropolitan Area.

TABLE 5 - 18 D.C. Metropolitan Area: Start and Extended Idle Emission Rates

Weighted	Passenger Car				Passenger Truck			
age	CH4	N2O	CO2	CO2E	CH4	N2O	CO2	CO2E
0-3 year	0.280	0.856	605.113	677.185	0.397	1.160	786.046	884.202
4-6 year	0.333	0.856	605.115	678.293	0.527	1.176	784.166	886.487
>6 year	0.141	0.856	605.113	674.267	0.308	1.152	784.068	879.697

TABLE 5 - 19 D.C. Metropolitan Area: Running Emission Rates

Weighted	Passenger Car				Passenger Truck			
age	CH4	N2O	CO2	CO2E	CH4	N2O	CO2	CO2E
0-3 year	0.004	0.008	399.109	401.647	0.004	0.020	577.547	583.674
4-6 year	0.004	0.008	399.224	401.770	0.009	0.021	577.763	584.304
>6 year	0.004	0.008	399.340	401.893	0.008	0.020	579.010	585.320

5.6 Vehicle GHGEs of Households

The model system provides the estimations of households' vehicle type and vintage, vehicle quantity, annual VMT for each vehicle, and GHGEs rates look-up tables based on different vehicle type and vintage. Thus, the vehicle annual GHGEs can be calculated for each household (see 3.7).

FIGURE 5 - 7 Average vehicle annual GHGEs over household groups.

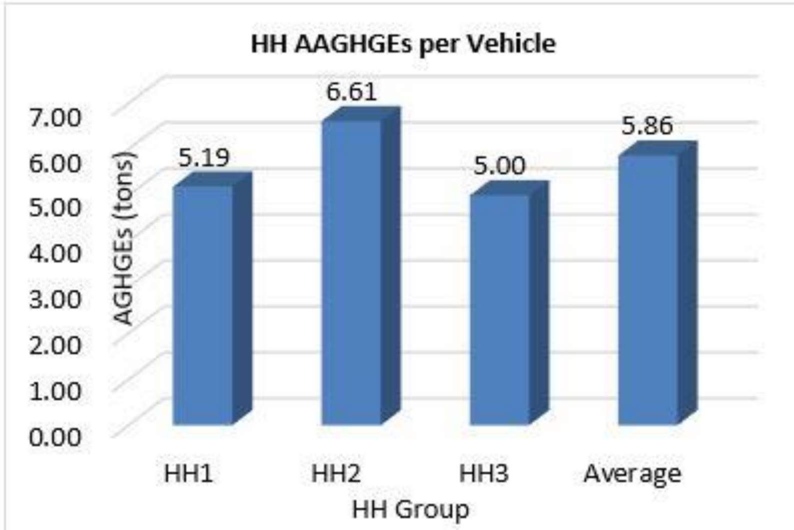
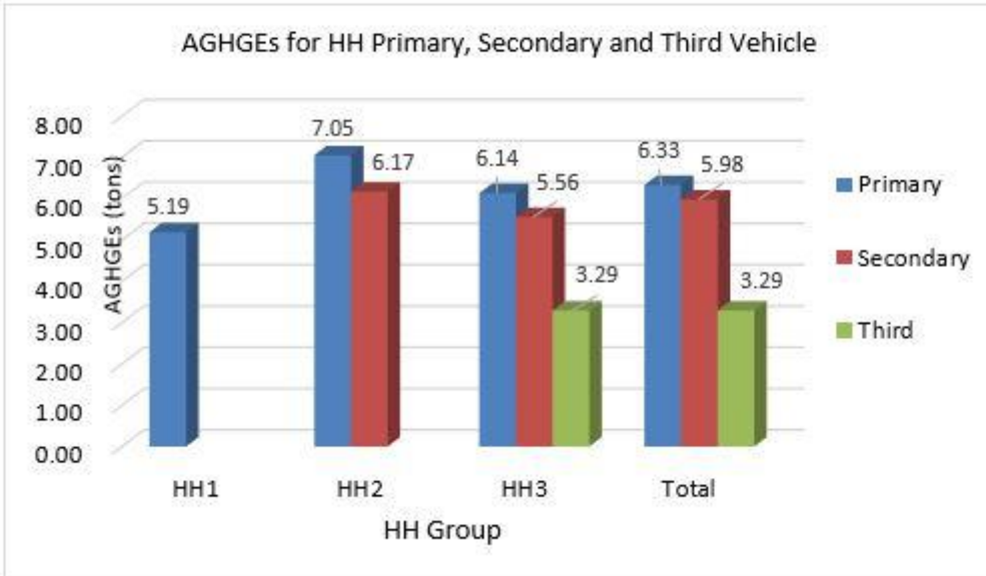


Figure 5-7 compares the average vehicle annual GHGEs over households with one, two and three vehicles. For households with one vehicle, the average annual GHG emission is about 5.2 tons which is consistent with the 2013 annual report from the EPA. Higher emission rates are calculated for households with more than one vehicle. For each household group, the average annual GHGEs have also been calculated for the primary, secondary and tertiary vehicles separately.

In Figure 5-8, the primary vehicles produce the highest GHGEs per year because they are more frequently driven by households. On the contrary, the tertiary vehicles produce the lowest GHGEs because they are not frequently driven by households. In addition, the pattern in Figure 5-8 shows that higher GHGEs from the primary vehicle if the household holds more vehicles. On the average, the annual GHGEs for households' primary, secondary and tertiary vehicles are 6.33 tons, 5.98 tons and 3.29 tons, respectively.

FIGURE 5 - 8 Annual GHGEs for households' primary, secondary and tertiary vehicles.

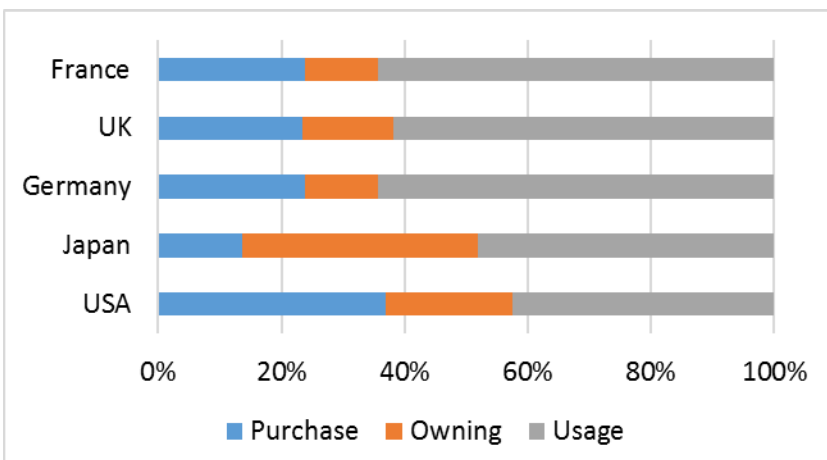


Chapter 6: Policy Analysis

6.1 Taxation Policy Plan

The model system described in Chapter 3 is applied to the Washington D.C. Metropolitan Area in order to estimate (a) the change of car ownership shares; (b) the change in car usage and (c) the change of households' annual GHGEs under different taxation policies. In developed countries, there are mainly three types of car-related taxes – purchase tax, ownership tax and fuel tax. Although the total amount of car-related tax is almost the same for countries like France, UK, Germany and Japan, the weight among tax components varies differently (*11*). In the US, about 80% of car-related taxes are purchase tax and fuel tax, the rest is mainly vehicle ownership tax. Therefore, we mainly discuss purchase tax, ownership tax and fuel tax in our analysis.

FIGURE 6 - 1 Shares of Car-related Taxes on the Standard Passenger Vehicles: International Comparison, 1997.10. (6)



From the 2009 NHTS data for the Washington D.C. Metropolitan Area, we calculate the average annual VMT, average driving cost and average purchase price.

The baseline values for our analysis are: (a) average annual vehicle miles traveled (AAVMT): 12021 miles; (b) average driving cost (ADC) per vehicle per mile: $0.154/mile and (c) average purchase price (APP) per vehicle: $9315. We assume that the average vehicle life (AVL) is 10 years and we ignore the inflation. The approach to determine equivalent policy plans for three different types of taxes has been illustrated below, AVT represents annual vehicle tax.

- Purchase taxes: three plans to increase vehicle price by 10%, 20%, 40% respectively

  Plan 1: AVT = APP * 10% / AVL = $9315 * 10% / 10 = $93.15

  Plan 2: AVT = APP * 20% / AVL = $9315 * 20% / 10 = $186.30

  Plan 3: AVT = APP * 40% / AVL = $9315 * 40% / 10 = $372.60

- Ownership taxes: three plans to charge an annual vehicle fee of $92.5, $185, $370 respectively

  Plan 1: subtract $92.5, $185, $277.5 from households' income for HH1, HH2, HH3 respectively

  Plan 2: subtract $185, $370, $555 from households' income for HH1, HH2, HH3 respectively

  Plan 3: subtract $370, $740, $1110 from households' income for HH1, HH2, HH3 respectively

- Fuel Taxes: three plans to increase driving/fuel cost by 5%, 10%, 20% respectively

  Plan 1: AVT = ADC * 5% * AAVMT = $0.154 * 5% * 12021 = $92.56

  Plan 2: AVT = ADC * 10% * AAVMT = $0.154 * 10% * 12021 = $185.12

Plan 3: AVT = ADC * 20% * AAVMT = $0.154 * 20% * 12021 = $370.25

For comparison purpose, we consider equivalent increments of $92.5, $185 and $370 additional annual fee for the three policy plans considered. Table 6-1 specifically shows how the three plans affect vehicle purchase price, households' income and fuel price.

TABLE 6 - 1 Taxation Policy Plan

Equivalent increment	Plan ID	Purchase tax	Ownership tax	Fuel tax
$92.5 / car & year	1	+ 10%	Income-$92.5/car	+ 5%
$185 / car & year	2	+ 20%	Income-$185/car	+ 10%
$ 370 / car & year	3	+ 40%	Income-$370/car	+ 20%

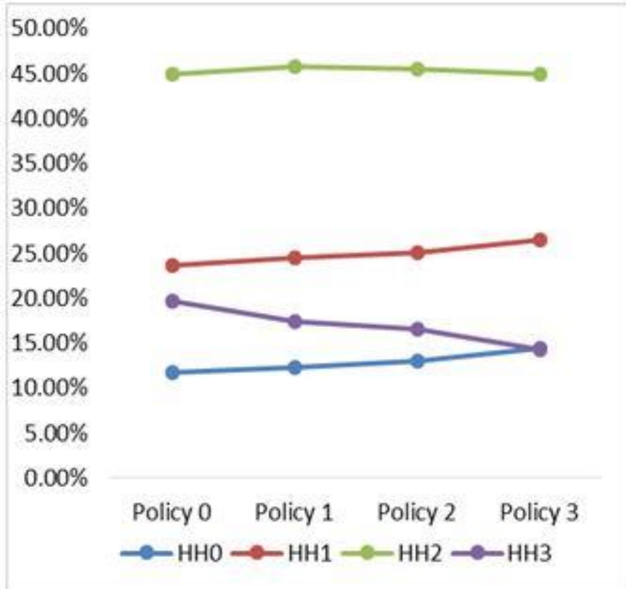
6.2 Sensitivity Analysis for Purchase Taxes

Purchase tax: an additional charge of $92.5, $185 and $370 annual fee per vehicle/year is applied; this is equivalent to increase vehicle purchase price by 10%, 20% and 40% respectively over one year. These plans are expected to reduce the number of vehicles owned by households in the study area especially for household groups with more vehicles. The scenarios can be summarized as follows:

- *Policy Plan 0*: Keep the current tax rates.
- *Policy Plan 1*: Increase the purchase tax by 10% of current vehicle price.
- *Policy Plan 2*: Increase the purchase tax by 20% of current vehicle price.
- *Policy Plan 3*: Increase the purchase tax by 40% of current vehicle price.

The shares of car ownership under the three policy plans are illustrated in Figure 6-2. As expected, the shares of households with two and three vehicles reduce while the shares of households with zero and one vehicle increase under the three policies. The pattern indicates that households tend to own fewer vehicles when purchase taxation policies are implemented.

FIGURE 6 - 2 Change of car ownership shares under purchase taxes.



The annual GHGEs reduction rates under three policy plans are showed in Figure 6-3. Different colors describe the emission reduction rates for HH1, HH2, HH3 and the entire population. We can observe that all three purchase taxes reduce annual GHGEs. For households with one and two vehicles, the reduction rates are small which indicate that these groups hold the number of vehicles to satisfy their basic travel and vehicle demands. On the contrary, the purchase taxes have a significant impact on households with three vehicles. The pattern in Figure 6-3 indicates that purchase taxes mainly reduce vehicle GHGEs by reducing car quantity for households' with more vehicles. On average, the implementation of the three policy plans will reduce the households' annual GHGEs by 2.3%, 3.6% and 7.8%, respectively.

FIGURE 6 - 3 GHGEs reduction under purchase taxes over HH groups.

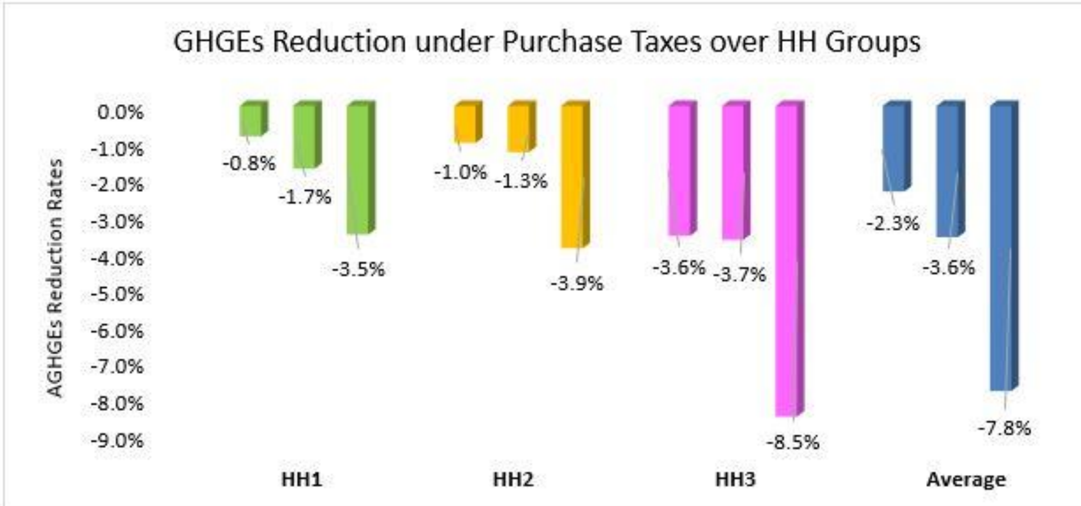
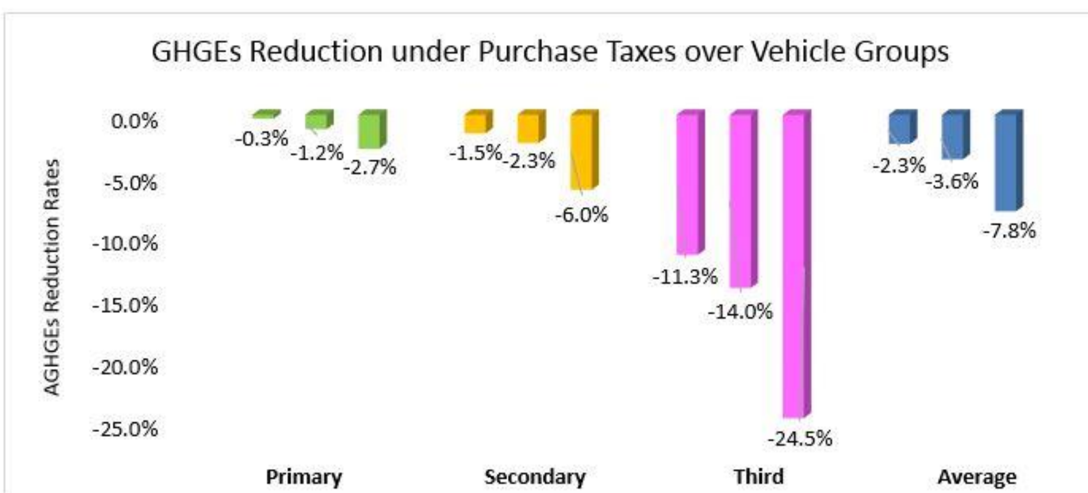


Figure 6-4 describes the GHGEs reduction under the three purchase taxes for households' primary, secondary and tertiary vehicles. For the primary and secondary vehicles, the reduction rates are small because households are highly dependent on traveling by cars. On the contrary, the purchase taxes have significant impact on households' tertiary vehicles, which indicates households are more likely to sell or stop driving their tertiary vehicles to reduce GHGEs under purchase taxes.

FIGURE 6 - 4 GHGEs reduction under purchase taxes over vehicle groups.



6.3 Sensitivity Analysis for Ownership Taxes

The ownership tax foresees an additional annual charge of $92.5, $185 and $370 per vehicle, which are equivalent to subtracting the vehicle annual fee from households' income. For households with one vehicle, we subtract $92.5, $185 and $370 respectively from their income under the three proposed policy plans. For households with two vehicles, we subtract $185, $370 and $740 respectively from their income under the three proposed policy plans. Similarly, for households with three vehicles, we subtract $277.5, $555 and $1110 respectively from their income under the three proposed policy plans. The ownership taxation policy plans are expected to reduce both vehicle quantity and vehicle usage and will have more significant impact on households with more vehicles. These scenarios are presented as follow:

- *Policy Plan 0*: No vehicle annual fee for ownership tax.
- *Policy Plan 1*: Charge an annual fee of $92.5 per vehicle for ownership tax.
- *Policy Plan 2*: Charge an annual fee of $185 per vehicle for ownership tax.
- *Policy Plan 3*: Charge an annual fee of $370 per vehicle for ownership tax.

The shares of car ownership under the three policy plans are illustrated in Table 6-2. We observe that the shares of households with three vehicles reduce while the shares of households with zero, one and two vehicles increase under the three policy plans. The pattern indicates that households, especially those with three vehicles, tend to own fewer vehicles when ownership taxation policies are implemented. On the average, the average car quantity decreases by 0.19%, 1.06% and 1.37% under the three policy plans.

TABLE 6 - 2 Change of Vehicle Ownership under Ownership Taxes

	0-car hh	1-car hh	2-car hh	3-car hh	Ave. car num.
Predicted	11.75%	23.61%	44.99%	19.65%	1.73
$92.5 ownership tax	11.69%	23.43%	45.40%	19.48%	1.73 -0.19%
$185 ownership tax	11.69%	24.08%	45.60%	18.63%	1.71 -1.06%
$370 ownership tax	11.48%	24.43%	46.06%	18.03%	1.71 -1.37%

The change of vehicle annual VMT for households' primary, secondary and tertiary vehicles under the three policy plans are described in Table 6-3. From the results, we can observe that the average annual VMT have more significant reductions for the primary vehicles under the three ownership taxes. On average, the annual VMT reductions for households' primary vehicles are 1.18%, 1.93% and 3.09% respectively. However, the average annual VMT reductions for households' secondary and tertiary vehicles are less than 1%.

TABLE 6 - 3 Change of Vehicle Usage under Ownership Taxes

	Primary vehicle mileage	Secondary vehicle mileage	Tertiary vehicle mileage
Predicted	12456.6	11755.8	9833.8
$92.5 ownership tax	12072.3 -1.18%	11680.9 -0.57%	9859.4 0.63%
$185 ownership tax	12216.1 -1.93%	11660.9 -0.81%	9783.9 -0.51%
$370 ownership tax	12072.3 -3.09%	11655.3 -0.85%	9790.4 -0.44%

The annual GHGEs reduction rates under three policy plans are showed in Figure 6-5. Different colors describe the emission reduction rates for HH1, HH2, HH3 and the entire population. We can observe that all three ownership taxes reduce annual GHGEs. The pattern in Figure 6-5 shows that owing tax has higher impact on reducing GHGEs for households with more vehicles. For households with one and two vehicles, the reduction rates are small which indicates that these groups hold the number of vehicles to satisfy their basic travel demands. On average, the implementation of the three owing taxes will reduce the households' annual GHGEs by 0.3%, 1.9% and 3.6%, respectively.

FIGURE 6 - 5 GHGEs reduction under ownership taxes over HH groups.

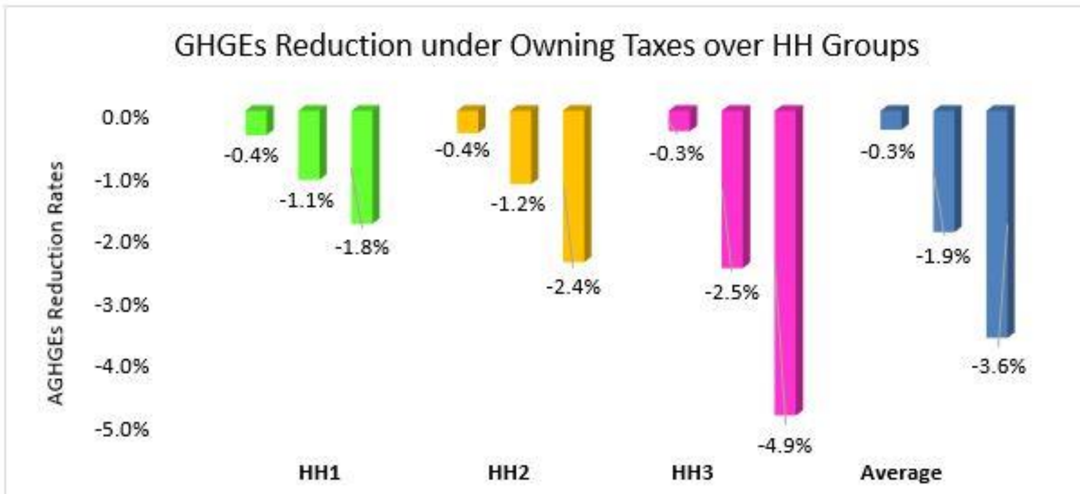
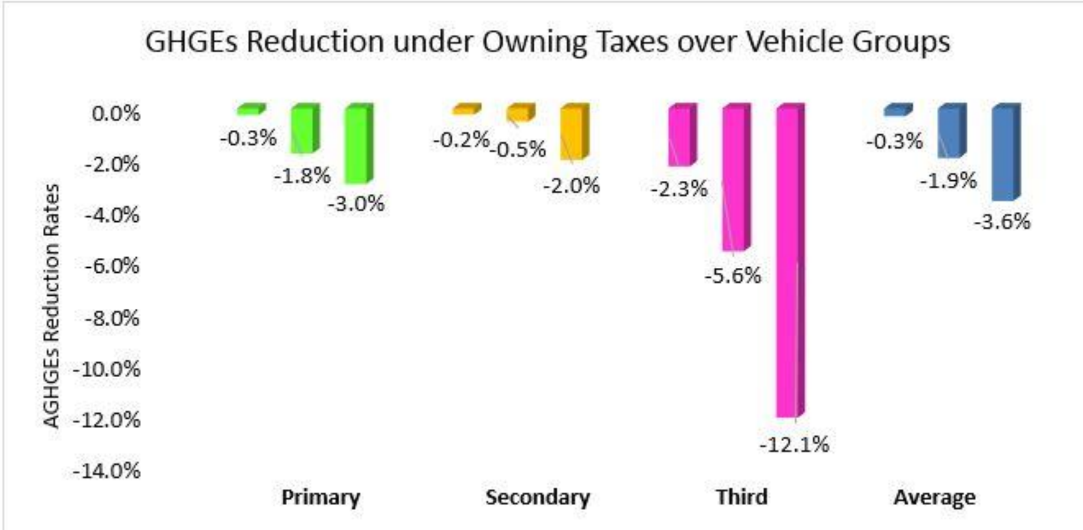


Figure 6-6 describes the GHGEs reduction under the three ownership taxes for households' primary, secondary and tertiary vehicles. For the primary and secondary vehicles, the reduction rates are small because households are highly dependent on traveling by cars. As expected, the ownership taxes have a significant impact on households' tertiary vehicles, indicating households are more likely to sell their tertiary vehicles to reduce the annual vehicle fee under ownership taxes.

FIGURE 6 - 6 GHGEs reduction under ownership taxes over vehicle groups.



6.4 Sensitivity Analysis for Fuel Taxes

The fuel tax foresees an additional annual charge of $92.5, $185 and $370 per vehicle, which are equivalent to an average increase of 5%, 10% and 20% of the driving cost. The fuel taxation policy plans are expected to reduce vehicle usage and will have a more significant impact on low-income households. These scenarios are presented as follow:

- *Policy Plan 0*: Keep the current tax rates.
- *Policy Plan 1*: Increase fuel price by 5%.
- *Policy Plan 2*: Increase fuel price by 10%.
- *Policy Plan 3*: Increase fuel price by 20%.

The change of vehicle annual VMT for different household groups under the three policy plans are presented in Figure 6-7. From the results, we can observe that the average annual VMT decreases under the three fuel taxes for each vehicle group.

There is no significant distinction for annual VMT decreasing rates between households' primary, secondary and tertiary vehicles.

FIGURE 6 - 7 Change of vehicle AVMT and GHGEs under usage tax.

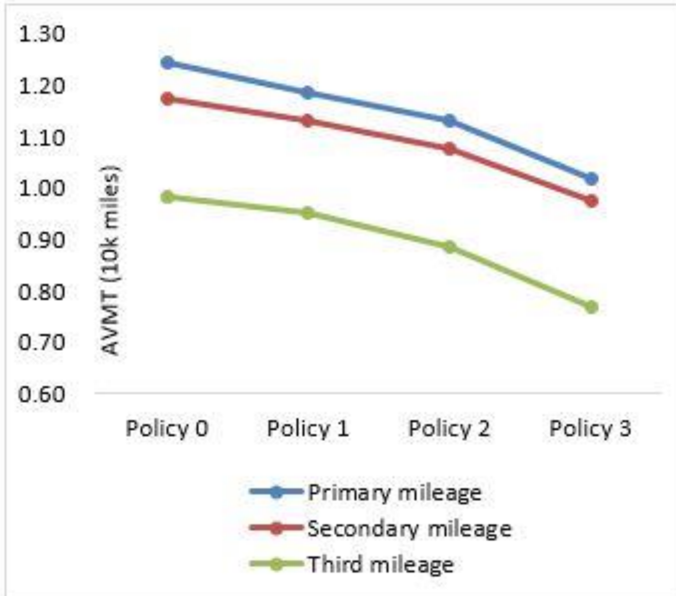


Figure 6-8 reports the annual GHGEs reduction under the proposed three fuel taxes. Different colors describe the emission reductions for HH1, HH2, HH3 and the entire population, respectively. We can observe that there is no significant difference for the emission reduction rates between different household groups. More specifically, the annual GHG emission reduction rates are slightly higher for households with smaller number of vehicles. For example, when we increase fuel price by 20%, the GHGEs of HH1, HH2 and HH3 reduce by 18.7%, 17.8% and 15.2%. On average, the implementation of the three policy plans will reduce the annual GHGEs by 3.2%, 8.1% and 16.8%, respectively.

FIGURE 6 - 8 GHGEs reduction under fuel taxes over HH groups.

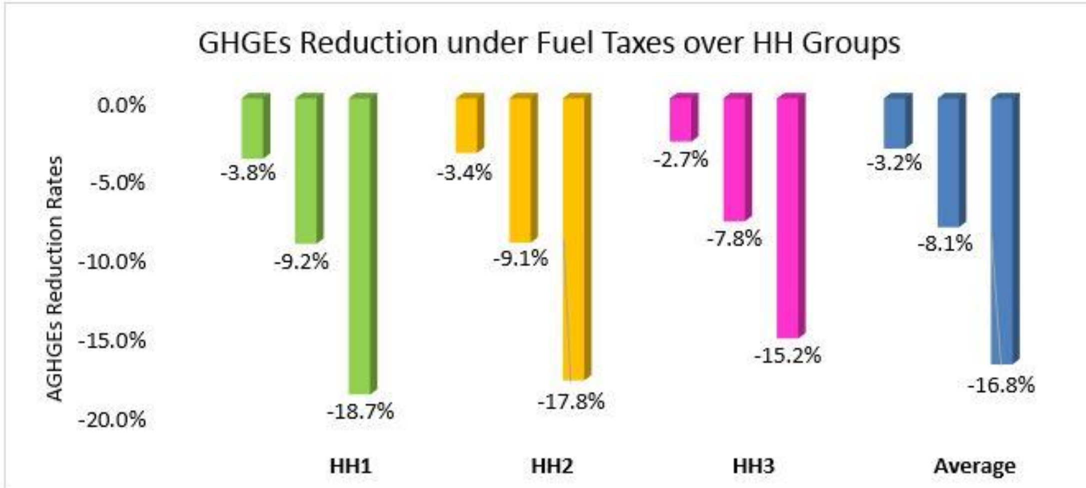
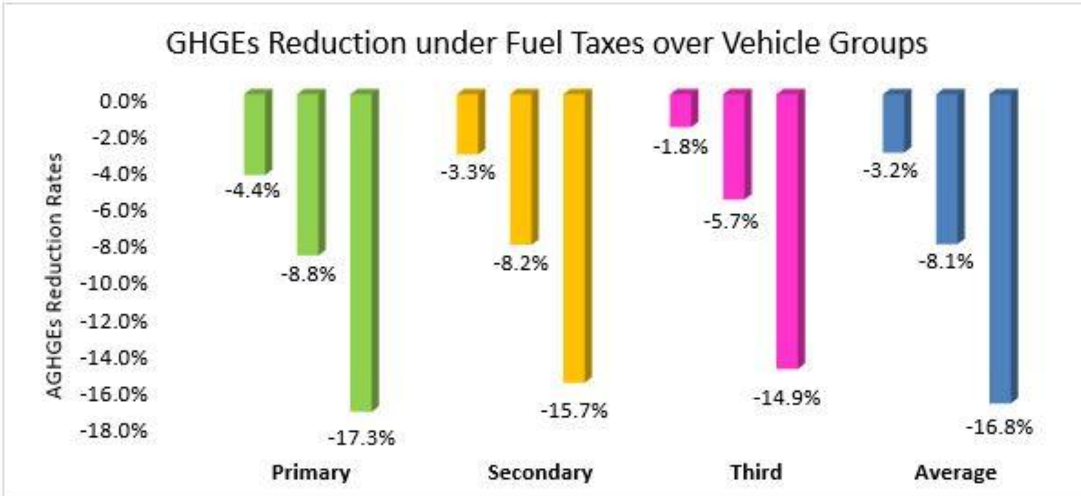


Figure 6-9 describes the GHGEs reduction under the three fuel taxes for households' primary, secondary and tertiary vehicles. The emission reduction rates are significant for three vehicle groups. More specifically, the impact on reducing GHGEs from fuel taxes is slightly higher for households' primary vehicles. In contrast, the impact on reducing GHGEs from fuel taxes is slightly lower for households' tertiary vehicles. This pattern indicates households are more likely to drive less by all of their holding vehicles, especially for the primary one, to reduce GHGEs under fuel taxation policies.

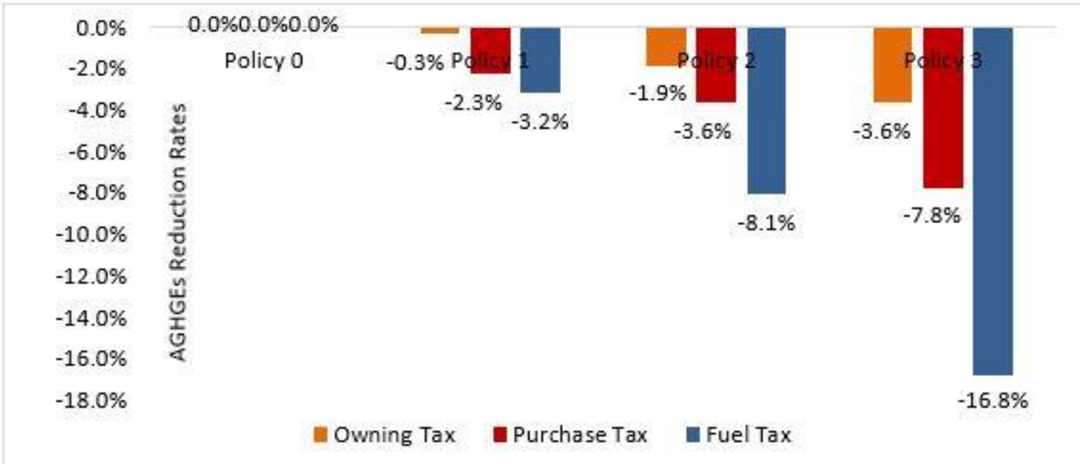
FIGURE 6 - 9 GHGEs reduction under fuel taxes over vehicle groups.



<u>6.5 Comparison of Impacts among Three Different Taxes</u>

Figure 6-10 compares the effects of ownership taxes, purchase taxes and fuel taxes on households' annual GHGEs under the three proposed policy plans. The fuel taxes have the highest impact on reducing annual GHGEs, followed by purchase taxes, and ownership taxes have the lowest impact to reduce GHGEs. Under policy plan 1, households' annual GHGEs will be reduced by 0.3%, 2.3% or 3.2% if ownership tax, purchase tax or fuel tax is implemented. Under policy plan 2, households' annual GHGEs will be reduced by 1.9%, 3.6% or 8.1% if ownership tax, purchase tax or fuel tax is implemented. Under policy plan 3, households' annual GHGEs will be reduced by 3.6%, 7.8% or 18.8% if ownership tax, purchase tax or fuel tax is implemented.

FIGURE 6 - 10 Comparison between ownership tax, purchase tax and fuel tax.



Chapter 7: Conclusions and Future Research

7.1 Conclusions

The proposed model system is designed to forecast vehicle GHGEs and to evaluate the effect of vehicle-related taxation schemes on household-level vehicle GHGEs. The model system is composed of four sub-models: (a) vehicle type and vintage choice; (b) vehicle quantity choice; (c) vehicle usage choice and (d) vehicle GHGES rates sub-model. A series of multinomial logit models are employed to estimate households' vehicle type and vintage decisions, while a multinomial probit model is proposed to estimate vehicle holding decisions. In order to estimate the annual VMT for each vehicle, the usage of households' primary, secondary and tertiary vehicles are estimated by three linear regression models respectively. The multinomial probit model and the three regression models are combined by an unrestricted full covariance matrix. Intuitively, an integrated discrete-continuous car ownership model is successfully applied to calculate households' vehicle quantity, type and usage behaviors while MOVES2014 is employed to estimate GHGEs rates for different types of vehicles.

Using MOVES2014, we estimate the GHGEs rates for the three representative counties selected by the cluster analysis in the Washington D.C. Metropolitan Area. Both start/extended idle emission rates look-up tables and running emission rates look-up tables are calculated for the three representative counties. The average emission rates look-up tables for the Washington D.C. Metropolitan Area are determined by taking the weighted average emission rates of the three counties.

Consequently, the household-level vehicle GHGEs are calculated from the estimated households' vehicle quantity, type and vintage, usage and emission rates look-up tables for different types of vehicles.

The variables considered in our model system are car characteristics, households' social demographics, land use variables, vehicle travel cost and county traffic condition variables. The model is estimated using the 2009 NHTS data and supplementary datasets from the *Consumer Report*, the *American Fact Finder*, the 2009 SMVR and MOVES default database.

The model system is applied to households with zero, one, two and three vehicles in the Washington D.C. Metropolitan Area. The coefficients estimated by the vehicle type, quantity and usage integrated discrete-continuous model are significant, yielding a generally good correspondence to the observed situation. The vehicle GHGEs rates calculated by MOVES2014 are slightly overestimated according to the assumptions.

Sensitivity analysis is conducted based on a series of equivalent increments of \$92.5, \$185 and \$370 annual fee per vehicle. The effects on reducing household-level GHGEs from ownership taxation policies, purchase taxation policies and fuel taxation policies have been tested. The results indicate that: (a) Fuel taxes are more effective to reduce GHGEs than ownership taxes and purchase taxes at different tax rates; (b) Fuel taxes have higher impacts on households with fewer vehicles. The policies mainly reduce GHGEs by decreasing households' vehicle usage, especially for low-income households; (c) Ownership taxes have the lowest impact on GHGEs reduction among the three different types of taxes. These policies reduce GHGEs by decreasing both households' vehicle quantity and usage; (d) Purchase taxes have higher impacts for households with more vehicles. These policies mainly reduce GHGEs by decreasing households' vehicle quantity.

7.2 Future Research

The thesis provides a pilot model system to estimate household-level vehicle GHGEs and proposes an application to the Washington D.C. Metropolitan Area. This work contributes to the estimation of household-level GHG emissions and provides quantitative results for policy aiming at reducing pollution from the transportation sector. The following points indicate possible avenues for future research.

The integrated model framework contains three linear regression models to estimate households' primary, secondary and tertiary vehicles. In reality, six linear regression models should be used to estimate the miles traveled for each vehicle – one regression for one-car households, two regressions for two-car households' primary and secondary vehicles, and three regressions for three-car households' primary, secondary and tertiary vehicles separately. This assumption can be relaxed if a larger sample size will be available in the future and if the computational complexity will be encompassed.

Another shortcoming of the model system is that all coefficients are assumed to be constant over different groups of households. Therefore, random parameter approach could be integrated into the framework to capture the taste variation among the population (*54*).

The results from the integrated model are estimated by numerical computation. The inverse of hessian matrix causes problems when computing standard errors of the estimates. We plan to use re-sampling techniques (such as bootstrapping) to estimate confidence interval of coefficients and therefore their significance.

The proposed model system is static and provides only short-term estimates and forecasts (*54*). It could be further extended into a dynamic model system to capture the household's annual GHGEs. For example, Xu (*59*) developed a dynamic vehicle ownership choice model which allows the estimation of the probability of buying a new vehicle or postponing this decision. If a decision is made to buy a new vehicle, the model further investigates the vehicle type choices. Because of the dynamic nature inherent from households’ GHGEs, the dynamic vehicle ownership model can improve our model system and provide policy makers guidance for medium to long term planning.

The estimated GHGEs rates from MOVES2014 depend highly on the assumptions which can be relaxed in the future for policy making in real projects. For example, in addition to gasoline, diesel vehicles and alternative fuel vehicles such as electricity and hybrid vehicles are relevant alternatives to be investigated for policy makers. In addition, the impact on households’ vehicle GHGEs from public transportation is also an interesting topic to be investigated in the future.

The thesis estimates households’ vehicle GHGEs by calculating GHGEs rates and vehicle annual miles traveled. Other methods can be employed to estimate households’ vehicle GHGEs for comparison purpose. For example, the GHGEs can be calculated from annual fuel consumptions and corresponding fuel economy (miles per gallon) for different types of vehicles.

The model system can be extended to different geographical areas to compare households' vehicle ownership behaviors and GHGEs. Therefore, appropriate policies can be proposed based on the unique characteristics of different geographical areas and household groups.

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