Evaluating policies to reduce greenhouse gas emissions from private transportation

Yan Liu, Cinzia Cirillo[1]
Department of Civil and Environmental Engineering, University of Maryland, College Park, MD 20742, USA

ABSTRACT

This paper proposes a model system to forecast household greenhouse gas emissions (GHGEs) from private transportation and to evaluate the effects of vehicle-related taxation policies on emission reductions. The proposed model successfully combines an integrated discrete-continuous car ownership model with the Motor Vehicle Emission Simulator 2014 (MOVES2014). Four modeling components are calibrated and applied to the calculation of GHGEs: households' choices of vehicle type and vintage, vehicle quantity, miles traveled, and rates of GHGEs for different vehicle types. The model is 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 State Motor Vehicle Registrations (SMVR) are used for the estimation. Three tax schemes: vehicle ownership tax, purchase tax and fuel tax are evaluated and their impacts on emission reductions are predicted. We calculate that in the study area the average GHGEs per vehicle is 5.79 tons of carbon dioxide-equivalent (CO_2E) gases. Our results show that: (a) a fuel tax is the most effective way to reduce vehicle GHGEs, especially for households with fewer vehicles; (b) a purchase tax reduces vehicle GHGEs mainly by decreasing vehicle quantity for households with more vehicles; and (c) an ownership tax reduces vehicle GHGEs by decreasing both vehicle quantity and miles traveled.

Keywords: discrete-continuous car ownership models, vehicle type choice, vehicle miles traveled (VMT), Motor Vehicle Emission Simulator (MOVES), greenhouse gas emissions, taxation policy

[1] Corresponding author's address: 3250 Kim Building, College Park, MD 20742, USA. Tel: +1 301 405 6864. E-mail addresses: yliu89@umd.edu (Y. Liu), ccirillo@umd.edu (C. Cirillo).

Introduction

Rising levels of carbon dioxide and other heat-trapping gases in the atmosphere are believed to warm the Earth and to cause wide-ranging impacts. In the long term, scientists project that these trends will continue and in some cases accelerate, posing significant risks to human health and to other natural resources that are vital to the environment. Societies around the globe need to reduce human-caused greenhouse gas emissions (GHGEs) to avoid worsening climate impacts and to reduce the risk of creating changes beyond our ability to respond and adapt. Policies are needed in order to reduce energy use, limit GHGEs, and build a clean energy economy (Department of Ecology, 2015).

According to the annual report of the United Nations Framework Convention on Climate Change (UNFCCC), in the United States (US) more than 27% of total GHGEs are from the transportation sector. Within this sector, light-duty vehicles are the largest pollutant sources, accounting for 61% of the total GHGEs (EPA, 2013). The estimation from the Organization for Economic Co-operation and Development (OECD) also shows that on-road passenger cars are responsible for around 15% of fossil fuel-related carbon dioxide (CO_2) emissions which are the main component of greenhouse gases (GHGs) (Dargay and Gately, 1997). Although mobile sources contribute large percentages of GHGEs, technology is not yet available to measure and tax emissions from each vehicle (Feng et al., 2005). Therefore, it is necessary to develop and apply effective and quantitative methodologies to support public authority decision making (Liu et al., 2014) and to analyze the impact of taxation policies on reductions of GHGEs.

GHGEs from light-duty vehicles are closely linked to households' car purchasing and driving behaviors. Preferences on vehicle type and quantity (i.e. the number of vehicles within households) determine car purchases, while driving behavior is best described by households' travel demand or vehicle usage (i.e. vehicle miles traveled, VMT). Therefore, the combination of the number of vehicles owned by a household, vehicle type, and the usage (i.e. VMT) of vehicles is an important determinant of households' vehicle GHGEs and fuel consumption (Vyas et al., 2012). The state-of-the-art in calculating GHGEs from vehicle usage 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) (Feng et al., 2005; Fullerton, 2005; Fullerton and Gan, 2005; Musti and Kockelman, 2011). Other methods which estimate vehicle GHGEs combine demand models and emission simulators such as the EPA's MOBILE6, MOVES, or the EMFAC model developed for California.

To estimate GHGEs from private transportation, this paper proposes an integrated model framework that efficiently forecasts the number of vehicle within a household, vehicle type/vintage, annual miles traveled, and the emission rate of each vehicle. Different from previous research, this model framework is able to estimate the usage pattern of households' primary, secondary, and tertiary vehicles. More specifically, it predicts the VMT of each vehicle and forecasts individual vehicle's annual greenhouse gas (GHG) emissions. To the best of our knowledge, this research is the first to forecast households' vehicle emissions by combining an integrated discrete-continuous car ownership model and MOVES2014. Furthermore, the integrated model accounts for different types of attributes such as socio-demographics, built environment, travel costs, and road traffic conditions. The proposed study also evaluates several tax schemes by applying the model system to real data extracted from the 2009 U.S. NHTS for the Washington D.C. Metropolitan Area.

The remainder of this paper is organized as follows. Section 2 provides a review of the literature on integrated discrete-continuous car ownership models and on previous methods used to estimate vehicle GHGEs. This is followed by Section 3 where we present the proposed framework based on four modules: vehicle type and vintage choice, quantity choice, usage decision, and GHGEs rates estimator. Section 4 introduces data sources necessary for model estimations, while Section 5 presents model estimation and validation results. In Section 6, three different taxation policies are evaluated and their effects to reduce GHGEs are compared. The final Section offers the concluding remarks and avenues for future research.

Literature Review

In this section we briefly cover previous studies on vehicle ownership and usage modeling, and we provide main features of existing emission simulators. Additionally, we outline the results obtained from policy analyses on energy and environmental related issues arising from private transportation.

Existing studies in the transportation literature about car ownership modeling attest that vehicle quantity, type/vintage, and usage are the main determinants needed for the calculation of fuel consumption, GHGEs, and other pollutants from private vehicles (Train, 1986). Moreover, researchers have recognized that those decisions are taken simultaneously and that integrated model should be used to model these decisions jointly (Dubin and McFadden, 1984; Hanemann, 1984). The early discrete-continuous models are derived from the conditional indirect utility function and are consistent with the microeconomic theory (Mannering and Winston, 1985; Jong, 1989). More recently, Bhat (Bhat, 2005) has developed multiple discrete-continuous extreme value (MDCEV) models that jointly estimate the holdings and usage of multiple vehicle types by households. Several variables were found to be significant for this problem: socio-demographic variables, built environment attributes, vehicle characteristics, and gasoline prices (Bhat and Sen, 2006; Bhat et al., 2009). However, Bhat's model is restricted by the assumption of fixed total miles traveled by each household. Fang (Fang, 2008) proposed a Bayesian Multivariate Ordered Probit and Tobit (BMOPT) model to estimate households' vehicle type, quantity, and usage. An ordered probit model was employed to determine households' decisions on the number of passenger cars and trucks. A multivariate tobit model was applied to estimate household decisions on VMT. The author concluded that the model was appropriate for predicting changes of vehicle quantity, types, and miles traveled. Liu et al. (2014) also developed an integrated discrete-continuous car ownership model that jointly estimated households' vehicle quantity, type, and usage. A multinomial probit model was employed to estimate vehicle quantity while a linear regression model was used to estimate total VMT of each household. The correlation among the discrete and the continuous parts was captured by an unrestricted full variance-covariance matrix of the unobserved factors.

Several emission estimation simulators have been developed and utilized to calculate GHGEs from private vehicles. For instances, the California's Emission Factors model

(EMFAC7F), the EPA's Vehicle Emission Modeling software (MOBILE5a), and the EPA's MOVES model (EPA, 1998). According to Bai et al. (2009), MOVES should be preferred to other software for the following reasons: (a) it combines vehicle specific power (VSP) and speed bins, rather than speed correction factors, to quantify running exhaust emissions; (b) it uses vehicle operating time rather than VMT as the unit of measure for various vehicle activities and emissions; and (c) it uses a relational database to manipulate data and enables multi-scale emission analyses and applications from link-level to nation-level.

A significant number of policy-oriented studies have explored market incentives that could be considered to reduce emissions (Eskeland and Devarajan, 1996). Dargay and Gately (1997) applied a car ownership model to forecast the growth of household vehicle quantity to the year 2015 for the Organization for Economic Co-operation and Development (OECD) countries and to estimate the growth of energy demand and emissions. They forecasted fuel consumption and CO_2 emissions by estimating trends in car ownership, income, population, vehicle usage, fuel efficiency, and fuel price. Fullerton and Gan (2005) used data from the California Air Resources Board (CARB) on 672 vehicles of various types and ages to estimate miles per gallon (MPG) and emissions per mile (EPM) which were assumed to be a function of vehicle type, age, and number of cylinders. They calculated emissions by using the EPM and other estimates from a discrete-continuous car ownership model. Feng et al. (2005) developed a nested logit structure to model choices among different vehicle bundles, considering the miles traveled and the age of each vehicle as continuous choices. Estimates from the joint model were combined with information on MPG of new vehicles from the EPA's report, EPM from the CARB, and gas prices from the ACCRA cost of living indexes, to calculate vehicle emissions. Musti and Kockelman (2011) utilized a car ownership model to jointly estimate vehicle class and VMT on 596 households extracted from the 2001 NHTS. They translated the estimated VMT into GHGEs by using EPA's conversion factors and fuel economy assumptions (EPA, 2007). Vyas et al. (2012) proposed a joint MDCEV- multinomial logit (MNL) model to estimate households' vehicle quantity, type, annual mileage, and the primary driver for each vehicle. The estimated vehicle type and quantity served as an engine for a household vehicle composition and evolution simulator which is embedded in a larger activity-based travel and emissions forecasting system - the Simulator of Activities, Greenhouse Emissions, Energy, Networks, and Travel (SimAGENT) (Goulias et al., 2012).

In addition, various tax schemes have been proposed and investigated to reduce GHGEs, among them we recall: vehicle purchase tax, vehicle ownership tax, tax on vehicle driving distance, emission tax, emission rates tax, fuel tax, tax on vehicle age, and tax on engine size (Fullerton, 2005). Distinct tax weights over different stages of car ownership will have tremendous influences on car purchasing behavior, driving patterns, and CO_2 emissions. In this context, Hayashi et al. (2001) proposed a model system that specifically determined effects of different components of taxation policies in the stages of (a) car purchase, (b) car owning, and (c) car usage. The model system was applied to analyze the impact of the 1989 tax reform in Japan and to forecast the future GHGEs reductions under different taxation schemes. Many researchers have found that fuel tax is the most effective strategy for reducing GHGEs among different vehicle-related taxes (Fullerton, 2005; Fullerton and Gan, 2005; Hayashi et al., 2001). For example, Davis and

Kilian (2009) calculated that an additional 10 cent gasoline tax per gallon would reduce vehicle carbon emissions by about 1.5% in the US. It should be noted that 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 (Musti and Kockelman, 2011; Cirillo et al., 2015).

The Model Framework

Structure of the Model System

The proposed framework accounts for households' decisions on vehicle quantity, type/vintage, and usage. Then it estimates GHGEs of each vehicle in a household. An integrated car ownership model, based on discrete choice models and regressions, is combined with MOVES to estimate GHGEs rates of different vehicle types. A flow chart of the modeling structure is given in Fig. 1.

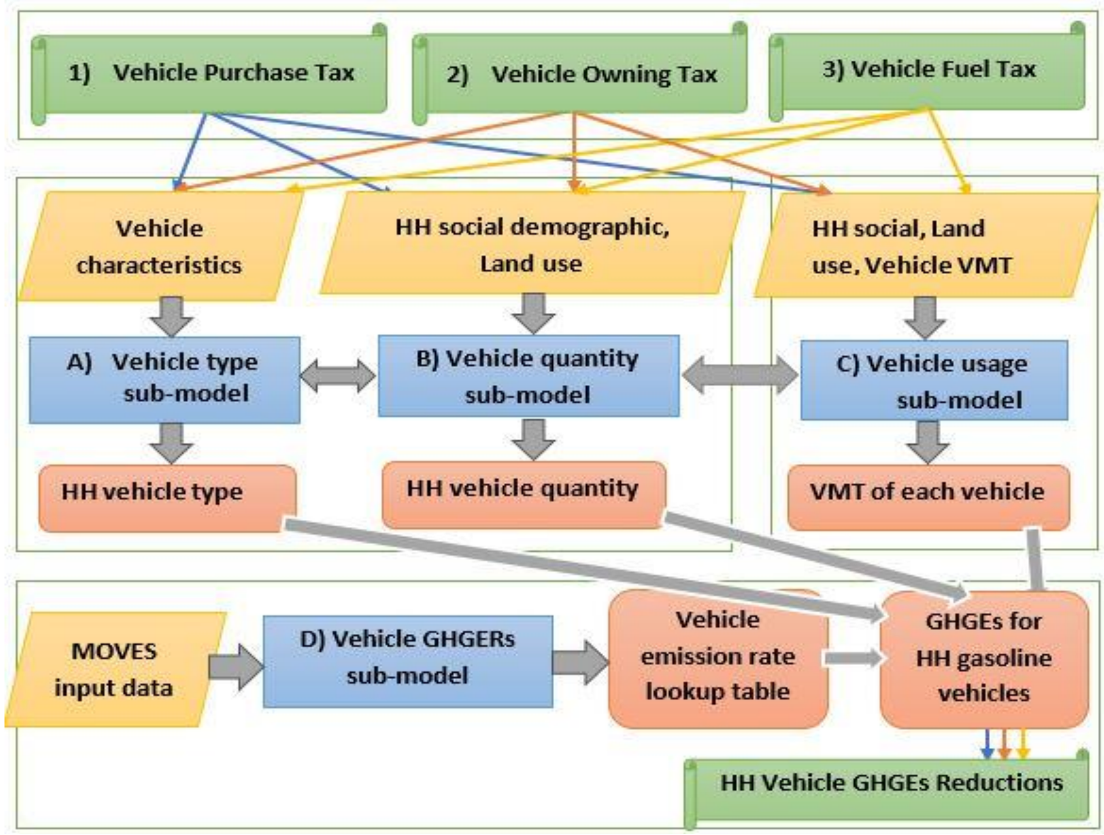


Fig. 1. Structure of the proposed model.

Specifically, the model structure includes four sub-models (in blue): (A) vehicle type logit model, (B) vehicle quantity probit model, (C) car usage (VMT) regression for each vehicle in a household, and (D) vehicle GHGEs rates estimation. The attributes (in yellow) considered are vehicle characteristics, households' social demographics, land use variables, and vehicle traveling information (See Appendix A for a detailed description of the independent variables). Effects of three vehicle-related taxes (in green) are evaluated in terms of GHGEs reductions due to their influences on households' discrete choices of vehicle quantity/type and continuous choices of annual VMT.

Vehicle Type and Vintage Sub-model

We adopt MNL models to capture households' decisions on vehicle type and vintage which are combinations of two types (passenger car and passenger truck) and three vintages (less than 3 years, 3-6 years, and older than 6 years). Let t_j ($j = 1, 2, 3$) represents the choice set of all combinations of vehicle types for households with j vehicles. U_{t_j} represents the indirect utility of choosing any vehicle type t_j' among the full choice set t_j.

$$U_{t_j} = V_{t_j} + \varepsilon_{t_j}, \quad \varepsilon_{t_j} \sim_{iid} \mathrm{EV1}(0, \lambda) \tag{1}$$

$$V_{t_j} = X_{t_j}^T \beta_{t_j} \tag{2}$$

where V_{t_j} and ε_{t_j} are observed and unobserved (error terms) parts of the utility functions. X_{t_j} represents the independent variables related to car characteristics, β_{t_j} are the parameters to be estimated. The error term, ε_{t_j}, is independent and identically distributed (IID) and follows type 1 extreme value (EV1) distribution. λ is a scale parameter normalized to 1.

Vehicle Quantity Sub-model

We employ multinomial probit (MNP) model to forecast households' decisions on vehicle quantity (Liu et al., 2014); the choice set includes four alternatives: owning zero, one, two, and three or more vehicles. The utility function of the vehicle quantity model consists of three parts - the observed utility of vehicle quantity choice (V_j) regardless of vehicle type choice, the information from vehicle type choice (r_j) given j vehicles, and the unobserved error term (ε_j).

$$U_j = V_j + \alpha r_j + \varepsilon_j \quad, \varepsilon_j \sim_{iid} \mathrm{N}(0, \sigma^2)\,, j = 0, 1, 2, 3 \tag{3}$$

$$V_j = X_j^T \beta_j \tag{4}$$

$$r_j = \mathrm{g}(max(U_{t_j})) \tag{5}$$

where U_j is the utility of vehicle quantity choice. X_j is the vector of variables contributing to vehicle quantity choice. $\mathrm{g}(*)$ is a statistical function of $max\ (U_{t_j})$, where U_{t_j} are the utilities of the vehicle type/vintage model, and α and β_j are parameters to be estimated.

To specify the information from vehicle type choice given j vehicles, we need to define the distribution of $max(U_{t_j})$.

$$\text{Let } v_j = max(U_{t_j})$$

Because vehicle type choice is estimated by MNL model, v_j follows type 1 extreme value (EV1) distribution with cumulative distribution (F_v) and probability density functions (f_v) as follows (Melnikov, 2013):

$$F_v(u;\, r_j) = \exp\left(-e^{-(u-r_j)}\right) \tag{6}$$

$$f_v(u;\, r_j) = e^{r_j}\exp\left(-e^{-(u-r_j)} - u\right) \tag{7}$$

where r_j is the mode of the following distribution (Melnikov, 2013) for the detail of this formulation):

$$r_j = lnG\left(\exp\left(V_{t_j}\right)\right) \tag{8}$$

where $G\left(V_{t_j}\right) = \sum_{t_j} V_{t_j}$ for MNL model with a Gumbel-distributed error term. Thus, r_j can be alternatively represented as follows:

$$r_j = ln\sum_{t_j}\exp\,(V_{t_j}) = E_j\left[max(U_{t_j})\right] \tag{9}$$

where $E_j(*)$ is the conditional expectation given j vehicles. The utility of vehicle quantity can be further written as:

$$\begin{aligned} U_0 &= \varepsilon_0 \\ U_1 &= V_1 + \alpha r_1 + \varepsilon_1 \\ U_2 &= V_2 + \alpha r_2 + \varepsilon_2 \\ U_3 &= V_3 + \alpha r_3 + \varepsilon_3 \end{aligned} \tag{10}$$

We assume the error terms follow a multivariate normal distribution with a full, unrestricted covariance matrix. Households are assumed to be rational and make decisions based on utility maximization rule.

For identification purpose, we take the difference of utility. Let $\widetilde{U}_{jy} = U_j - U_y$, $\tilde{V}_{jy} = (\alpha r_j + V_j) - (\alpha r_y + V_y)$, $\tilde{\varepsilon}_{jy} = \varepsilon_j - \varepsilon_y$. The differences of error terms, $\tilde{\varepsilon}_{jy}$, follow normal distributions. Then, the utility in difference is:

$$\widetilde{U}_{jy} = \tilde{V}_{jy} + \tilde{\varepsilon}_{jy} \tag{11}$$

where the subscript y represents the chosen alternative and j represents any alternative within the choice set. Let Y_{disc} represents households' decisions on vehicle quantity. The likelihood of choosing certain number of vehicles can be calculated as follows:

$$\mathrm{P}(Y_{disc} = \mathrm{y}) = \int_{R^3} I(\tilde{V}_{jy} + \tilde{\varepsilon}_{jy} < 0, \forall j \neq y)\varphi(\tilde{\varepsilon}_{jy})\, d\tilde{\varepsilon}_{jy} \tag{12}$$

where $I(*)$ is a function indicating that the chosen alternative y has the maximum utility among the choice set. $\varphi(*)$ is the density function of normal distribution. R^3indicates the dimension of integrals over $\tilde{\varepsilon}_{jy}$.

Vehicle Usage Sub-model

We use linear regression models to estimate households' vehicle usage pattern. Three regressions are used for households' primary, secondary, and tertiary vehicles.

$$Y_{VMT,s} = X_s^T \beta_s + \varepsilon_s \ , \varepsilon_s \sim N(0, \sigma_s^2) \quad (13)$$
$$s \in \{primary, scondary, tertiary\}$$

where $Y_{VMT,s}$ are the dependent variables describing annual miles traveled of each vehicle. X_s represents a vector of explanatory variables while β_s is a vector of corresponding coefficients to be estimated. $\varepsilon_s$is the error term. The regressions are solved with maximum likelihood method (McCulloch et al., 2008). For households with j vehicles, given:

$$Y_{VMT} = \left(Y_{VMT,1st}, Y_{VMT,2nd}, \dots \dots, Y_{VMT,jth}\right) \quad (14)$$

$$X = (X_{1st}, X_{2nd}, \dots \dots, X_{jth})$$

$$\beta = (\beta_{1st}, \beta_{2nd}, \dots \dots, \beta_{jth})$$

$$\varepsilon_{VMT} = (\varepsilon_{1st}, \varepsilon_{2nd}, \dots \dots, \varepsilon_{jth})$$

$$\varepsilon_{VMT} \sim \mathrm{N}(0, \Sigma_j)$$

$$\mathrm{j} = 1, 2, 3$$

where $Y_{VMT,jth}$ represents the continuous choice on households' VMT of the jth vehicle. $X_{jth}$is a vector of explanatory variables deciding the VMT of the jth vehicle, and β_{jth} is a vector of the corresponding coefficients. $\varepsilon_{VMT}$is the unobserved error term. $\Sigma_j$is the variance-covariance matrix of size j $\times$ j. The mileage of different vehicles within one household is jointly estimated by assuming that the error terms of different regressions follow a multivariate normal distribution centered at $X^T\beta$. Therefore, the likelihood of observing Y_{VMT} follows a multivariate normal density function:

$$\mathrm{P}\left(Y_{VMT} \middle| X, \beta, \Sigma_j\right) = \varphi\left(Y_{VMT} \middle| X^T\beta, \Sigma_j\right) \quad (15)$$

Instrumental variable (IV) approach, rather than ordinary least squares (OLS), is applied to avoid endogeneity problem due to the inclusion of the driving cost of the household's vehicle as an explanatory variable. Since a household chooses which vehicle it owns, it effectively chooses the driving cost that it faces. Therefore, the driving cost that a household faces is an endogenous variable, and estimation with ordinary least squares is biased (Train, 1986). Specifically, we employ the two-stage least squares (2SLS) method to solve the endogeneity problem. In the first stage, the exogenous variables used to predict driving cost are gas price in the residential area, household income, number of workers, living in urban area, age of household head, education level of household head, gender of household head, and residential density. In the second stage, we consider household income, residential density, household head gender, and the estimated driving cost (from the first stage) to forecast annual VMT of households' primary, secondary, and tertiary vehicles.

Integrated Discrete-Continuous Choice Model

To capture the correlations between households' discrete and continuous choices, we estimate Y_{disc} and Y_{VMT} jointly. Taking advantage of the fact that both error terms of the regression model and the probit model follow normal distributions, the combination of error terms from the two parts will follow a multivariate normal (MVN) distribution.

$$(\tilde{\varepsilon}_{10}, \tilde{\varepsilon}_{20}, \tilde{\varepsilon}_{30}, \varepsilon_{VMT}) = \left(\tilde{\varepsilon}_{10}, \tilde{\varepsilon}_{20}, \tilde{\varepsilon}_{30}, \varepsilon_{1st}, \varepsilon_{2nd}, \dots \dots, \varepsilon_{jth}\right) \sim MVN\left(0, \Sigma_{3+j}\right), j = 1, 2, 3 \tag{16}$$

$\tilde{\varepsilon}_{10}, \tilde{\varepsilon}_{20}, \tilde{\varepsilon}_{30}$represent error terms in difference of the probit model respective to zero-vehicle households. $\varepsilon_{jth}$is the error term of households' VMT of the jth vehicle. We integrate discrete and continuous parts by assuming a full, unrestricted variance-covariance matrix. The dimension of the matrix is $(3 + j) \times (3 + j)$. The number of vehicles j vary across different households.

Liu's simulation results (Liu, 2013) show that the joint probability $P(Y_{disc}, Y_{VMT})$ is more appropriate to be expressed as the product of the marginal probability of driving certain miles $P(Y_{VMT})$ and the conditional probability of choosing the number of vehicles based on VMT $P(Y_{disc}|Y_{VMT})$.

$$P(Y_{disc}, Y_{VMT}) = P(Y_{VMT})P(Y_{disc}|Y_{VMT}) \tag{17}$$

The second part follows a MVN distribution with new mean and variance-covariance matrix.

$$\text{If } \begin{bmatrix} \varepsilon_{disc} \\ \varepsilon_{VMT} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \Sigma_{disc} & \Sigma_{disc,VMT} \\ \Sigma_{VMT,disc} & \Sigma_{VMT} \end{bmatrix}\right) \tag{18}$$

$$\text{Then } \varepsilon_{disc,VMT} \sim N(0 + \frac{\Sigma_{disc,VMT}}{\Sigma_{VMT}}(err - 0)\,,\ \Sigma_{disc} - \frac{\Sigma_{disc,VMT}\,\Sigma_{VMT,disc}}{\Sigma_{VMT}})$$

where $\varepsilon_{disc,VMT}$is the integrated error term, and err represents observed errors.

Vehicle GHGEs Rates Sub-model

We employ MOVES2014 to estimate vehicle emission rates for the main components of GHGs - CO_2, methane (CH_4), and nitrous oxide (N_2O) emitted from vehicle tailpipe. The amounts of CH_4 and N_2O emissions are less than CO_2, however, these gases have higher potential global warming effects (EPA, 2011). Thus, emission rates of all gases are transformed into carbon dioxide equivalent (CO_2E) gases for comparison purpose. Vehicle emission rates not only depend on vehicle characteristics (i.e. vehicle size and model year), but also depend on driving information (i.e. start time and speed), traffic condition (i.e. total number of vehicles and mileage), and environment factors (i.e. meteorology). We consider two vehicle types (passenger car and passenger truck) and three vintages (less than 3 years, 3-6 years, older than 6 years) which are consistent with the vehicle classification in the vehicle type sub-model. Vehicle GHGEs are from two driving processes – running process and start/extended idle process. The specific emission rates estimation flowchart is illustrated in Fig. 2.

The inputs of MOVES consist a run specification (Run Spec) and input data files. The run specification contains scenario description, scale, inventory or emission rates, time spans, geographic bounds, vehicles or equipment, road type, pollutants and processes, and output. Input data files, which correspond to the run specification, contain: (a) source type population; (b) vehicle type VMT; (c) maintenance 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.

In this research, we estimate vehicle emission rates for the Washington D.C. Metropolitan Area which 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. To avoid predicting emission rates for all eighteen counties, a cluster analysis is adopted to classify the counties into five groups based on the total number of vehicles and total mileage traveled in each county. Average vehicle emission rates for the Washington D.C. Metropolitan Area are calculated as a weighted average over five county groups. Besides, to forecast GHGEs for each household vehicle in the target area, we choose emission rates instead of inventory.

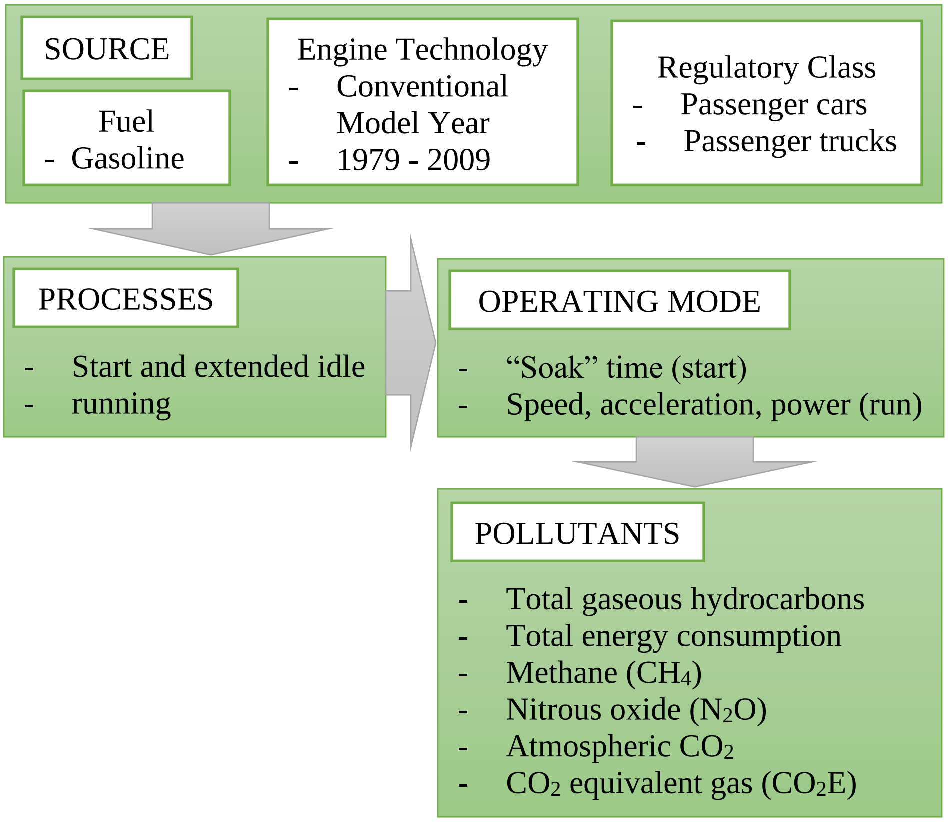


Fig. 2. Emission rates estimation flowchart (based on MOVES documentation).

Household Vehicle GHGEs Calculation

In our modeling framework, we obtain the information on households' vehicle type and vintage, quantity, annual miles traveled, running emission rates, and start/extended idle emission rates for different vehicle types. We then calculate annual GHGEs for each household vehicle according to the following formula:

$$AGHGEs\left(\frac{grams}{vehicle-year}\right) = RERs\left(\frac{grams}{vehicle-mile}\right) \times AVMT\left(\frac{miles}{year}\right) + SERs\left(\frac{grams}{vehicle-day}\right) \times D_s\left(\frac{days}{year}\right) \tag{19}$$

Where $AGHGEs$ is annual GHGEs. $RERs$ and $SERs$ represent running emission rates and start/extended idle emission rates, respectively. $AVMT$ represents annual VMT. D_s is the effective number of weekdays per year when vehicle s is utilized. D_s is calculated as follows:

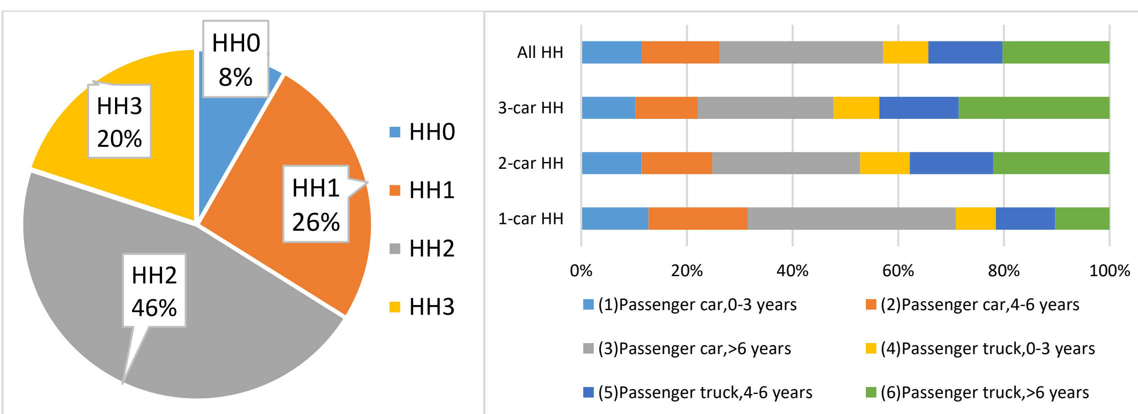
$$D_s\left(\frac{days}{year}\right) = W_d\left(\frac{days}{year}\right) \times \alpha_s + W_e\left(\frac{days}{year}\right) \times \beta_s \times \gamma \tag{20}$$

Where W_d equals 261, which is the number of weekdays in 2009; W_e equals 104, which is the number of weekends in 2009; α_s represents the utilization rate of vehicle s during weekdays, while β_s represents the utilization rate of vehicle s during weekends. γ

is a factor to scale from weekend emissions to weekday emissions, s represents households' primary, secondary, and tertiary vehicles. the scale factor from daily vehicle start emissions to annual vehicle start emissions. Although the number of driving days per year is not available for each households' vehicle, the NHTS sample in the Washington D.C. Metropolitan area provides 20,409 observations of individuals' daily activities from 2,218 households from April 2008 to April 2009. From this sample, the three factors in eq. 20 (α, β, and γ) were calculated.

Data Sources

The primary data source used for this research is the 2009 NHTS. After data processing and cleaning, 1289 household records are available for the study area. The data file mainly contains information for households' characteristics (i.e. income level, number of adults, number of workers, number of drivers, age, gender, education level, and etc.), car ownership (i.e. number of household cars, vehicle make, model, model year, and etc.), and land use (i.e. housing units per square mile, population per square mile, and etc.). Fig. 3 (1-5) shows descriptive statistics related to our sample in the Washington D.C. Metropolitan Area. The shares of households with zero, one, two, and three or more vehicles are 8.3%, 25.6%, 46.2%, and 19.9% respectively. The percentage of zero-vehicle households is 8.3%, higher than the national average 4.8%, due to high population density of the study area. The average number of vehicles per household is 1.77, slightly lower than the national average 1.91. Fig. 3 (2) illustrates the distribution of six different vehicle types which is consistent with vehicle type sub-model and MOVES. The figure shows that households with more vehicles tend to have higher percentage of passenger trucks than cars. Households with one vehicle prefer passenger cars (70%) to trucks (30%), while households with two or more vehicles have no obvious preference on passenger car or truck. Additionally, around half of the vehicles in the sample are older than six years.



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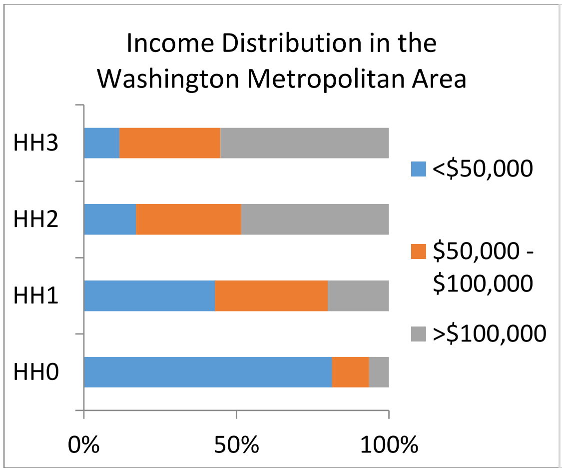

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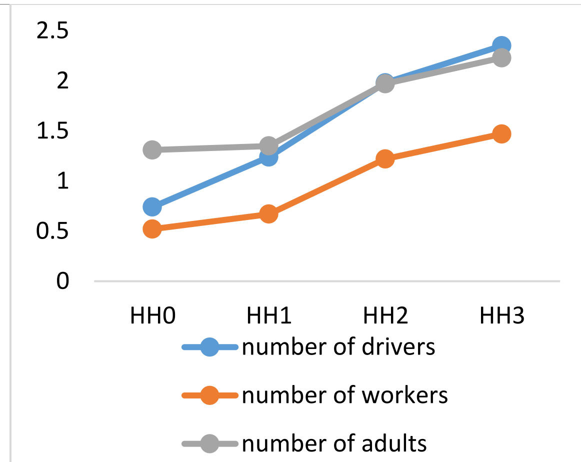

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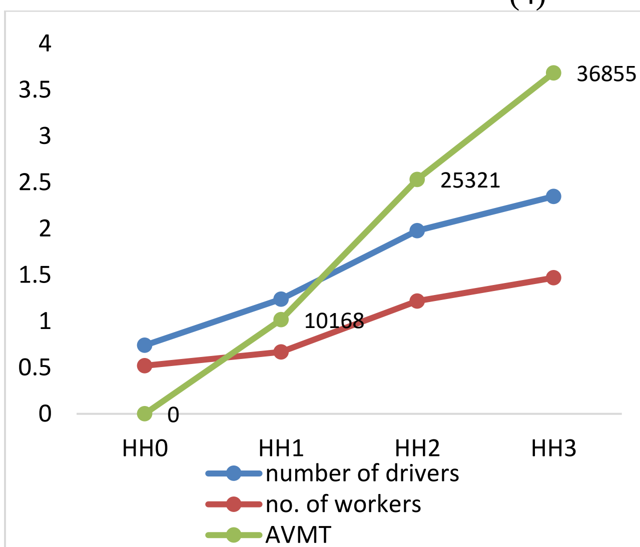


(5)

Fig. 3. Descriptive statistics of data in the Washington D.C. Metropolitan Area.

Households' socio-demographic and land use variables have great influence on car ownership and usage decisions. In the Washington D.C. Metropolitan Area, households' income and education level are higher than the national average. Households with more vehicles tend to have higher income level, as showed in Fig. 3 (3), and they tend to live in less dense or rural areas. In Fig. 3 (3-5), axes labeled "HH0", "HH1", "HH2", and "HH3" represent households with zero, one, two, and three vehicles respectively. Fig. 3 (4) describes the relationship between households' size and the number of workers, drivers, and adults. The vertical axes in Fig. 3 (4-5) represent the number of individuals. The number of workers, drivers, and annual VMT increase with households' size, as described in Fig. 3 (5).

The four supplementary data sources used in this study are the Consumer Reports, the American Fact Finder, the 2009 SMVR, and MOVES default database. Data from Consumer Reports provides vehicle characteristics including vehicle price, seating space, engine size, transmission, acceleration, shoulder room, etc., which are associated to vehicle type decisions. The American Fact Finder provides residential population, while the 2009 SMVR data gives vehicle population in the study area which is essential for emission rates estimation. Information on road condition and weather such as ramp and meteorology (temperature and humility) are derived from MOVES default database.

Model Estimation and Validation Results

Results for Integrated Discrete-Continuous Car Ownership Sub-Model

The framework of the integrated car ownership sub-model jointly estimates vehicle type, quantity, and annual miles traveled for households' primary, secondary, and tertiary vehicles. Primary vehicle is defined as the one used the most by a household while tertiary vehicle is the one used the least. We first calculate the mode of utilities from vehicle type logit model, which serves as a variable in the utility function of vehicle quantity choice. We estimate the integrated model on the sample of 1289 observations for the Washington D.C. Metropolitan Area. The number of observations for households' primary, secondary, and tertiary vehicles from the sample are 1182, 852, and 257 respectively. Table 1 reports estimation results of the integrated discrete-continuous model.

Table 1

Integrated discrete-continuous model: estimation results.

Variable	Alternative	Coefficient	Standard Deviation	p-value
Mode of type / vintage	all	0.801	0.123	<0.001
Constant	1 car	-6.492	0.886	<0.001
	2 cars	-19.880	1.269	<0.001
	3 cars	-24.995	1.114	<0.001
Low income	1 car	0.104	0.029	<0.001
	2 cars	0.227	0.040	<0.001
	3 cars	0.399	0.036	<0.001
Middle income	1 car	0.123	0.025	<0.001
	2 cars	0.266	0.052	<0.001
	3 cars	0.160	0.043	<0.001
High income	1 car	0.002	0.105	0.983
	2 cars	0.147	0.026	<0.001
	3 cars	0.100	0.026	<0.001
Number of drivers	1 car	1.101	0.624	0.078
	2 cars	2.961	0.837	<0.001
	3 cars	3.974	1.137	<0.001
Household head gender (1 for Male)	1 car	0.740	0.201	<0.001
	2 cars	1.262	0.638	0.048
	3 cars	1.360	0.358	<0.001
Residential Density / low income	1 car	-0.154	0.024	<0.001
	2 cars	-0.349	0.078	<0.001

	3 cars	-0.226	0.066	0.001
Residential Density / mid income	1 car	-0.191	0.036	<0.001
	2 cars	-0.314	0.035	<0.001
	3 cars	-0.482	0.048	<0.001
Residential Density / high income	1 car	-0.023	0.015	0.889
	2 cars	-0.329	0.075	<0.001
	3 cars	-0.598	0.055	<0.001
Constant	Regression for primary vehicle	5.020	1.406	<0.001
Income		0.059	0.027	<0.001
Household head gender		0.211	0.053	<0.001
Residential density		-0.046	0.009	<0.001
Driving cost		-2.944	0.737	<0.001
Constant	Regression for secondary vehicle	5.101	0.829	<0.001
Income		0.021	0.005	<0.001
Household head gender		-0.117	0.044	0.008
Residential density		-0.107	0.013	<0.001
Driving cost		-2.616	0.470	<0.001
Constant	Regression for tertiary vehicle	5.178	0.798	<0.001
Income		0.017	0.004	<0.001
Household head gender		-0.112	0.042	0.009
Residential density		-0.116	0.013	<0.001
Driving cost		-2.634	0.463	<0.001
Log-likelihood at zero	-3852.41			
Log-likelihood at convergence	-2898.16			
Number of observations	1289			
R square	0.248			

*Note: the model uses bootstrapping re-sampling method to calculate standard deviations.

The estimation results of the integrated model can be interpreted as follows. The "Mode of type/vintage" represents the expected maximum utility of choosing vehicle type and vintage. The corresponding parameter is significant and between zero and one.

The coefficients of households' income are positive which indicate that households with higher income tend to have more vehicles and drive more. For low-income group, the value of income coefficient is larger, indicating that income has higher impact for households with more vehicles. In addition, for three-car households, the value of income coefficient is larger for households with lower income, which indicates income has a higher impact on the low-income group.

The positive coefficients of the number of drivers indicate that households prefer to have more vehicles if there are more drivers within the households. This variable has higher impact on households with more vehicles.

The positive coefficients of household head gender indicate male household heads are more likely to have more vehicles and to drive the primary vehicle more frequently. The negative coefficients of household head gender in the regressions for secondary and tertiary vehicles show that females are more likely to drive the secondary and tertiary vehicles.

The negative coefficients of residential density indicate that households living in areas with higher population density prefer to have fewer vehicles and to drive less. Households living in suburban or rural areas are more likely to have more vehicles. In addition, for middle-income and high-income groups, the absolute value of residential density coefficient is higher, indicating higher impact for households with more vehicles.

The negative coefficients of driving cost indicate that households tend to drive less under higher fuel cost as expected. The values of the coefficients illustrate that the usage of primary car is more sensitive to fuel cost.

Car Ownership Sub-Model Validation

For validation purpose, the entire sample size has been divided into two parts; the estimation sample contains 80% of the population while the application sample contains the remaining 20% of the observations. We report the actual vehicle ownership and usage, the predicted vehicle ownership and usage, and their differences in Table 2. The results show that overall the model is able to reproduce actual choices but it slightly underestimates vehicle ownership and the average annual vehicle miles traveled (AAVMT).

Table 2
Joint discrete-continuous model: validation results.

		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	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%

Results for Vehicle GHGEs Rates Sub-Model

We employ MOVES2014 to estimate the average emission rates of the main components of greenhouse gases for the Washington D.C. Metropolitan Area. A cluster analysis is utilized to categorize eighteen counties in the target area into five groups based on factors such as vehicle population and total VMT in each county. The average GHGEs rates are calculated as the weighted average of emission rates over the five groups. Several assumptions are made for estimation: (a) the average annual GHGEs rates are the average emission rates of typical summer months (July and August) and typical winter months (January and February); (b) only gasoline vehicles are considered;

(c) we only consider emission rates for weekdays; (d) we assume the number of vehicles traveling in a county equals to the number of registered vehicles of that county.

GHGs emit during two driving processes – running process and start/extended idle process. We calculate emission rates and develop look-up tables for each of the two processes. Table 3 reports the weighted average running emission rates (grams per vehicle per mile) and Table 4 reports start/extended idle emission rates (grams per vehicle per day). We find that GHGEs rates are sensitive to factors such as speed and road type.

Table 3
Washington D.C. Metropolitan Area: running emission rates.

Weighted	Passenger Car				Passenger Truck			
age	CH_4	N_2O	CO_2	CO_2E	CH_4	N_2O	CO_2	CO_2E
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

Table 4
Washington D.C. Metropolitan Area: start and extended idle emission rates.

Weighted	Passenger Car				Passenger Truck			
age	CH_4	N_2O	CO_2	CO_2E	CH_4	N_2O	CO_2	CO_2E
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

The results show that in the Washington D.C. Metropolitan Area, the average running CO_2E emission rates for passenger car and truck are 402 grams/mile and 584 grams/mile respectively; and the average start/extended idle CO_2E emission rates for passenger car and truck is about 677 grams/day and 884 grams/day. The start/extended idle emission rates are higher for counties with higher vehicle population, while there is no significant variation for running emission rates over different counties. Moreover, the start/extended idle emission rates in winter are much higher than those in summer, which is reasonable due to longer start time and more fuel consumptions at low temperature (Mcmichael and Sigsby, 1966; Vijayaraghavan, 2012).

Results for Household Vehicle GHGEs

The estimations of households' vehicle type and vintage, vehicle quantity, annual VMT for each vehicle, and GHGEs rates for different vehicle types are then used to calculate households' average annual vehicle GHGEs (See equation 19).

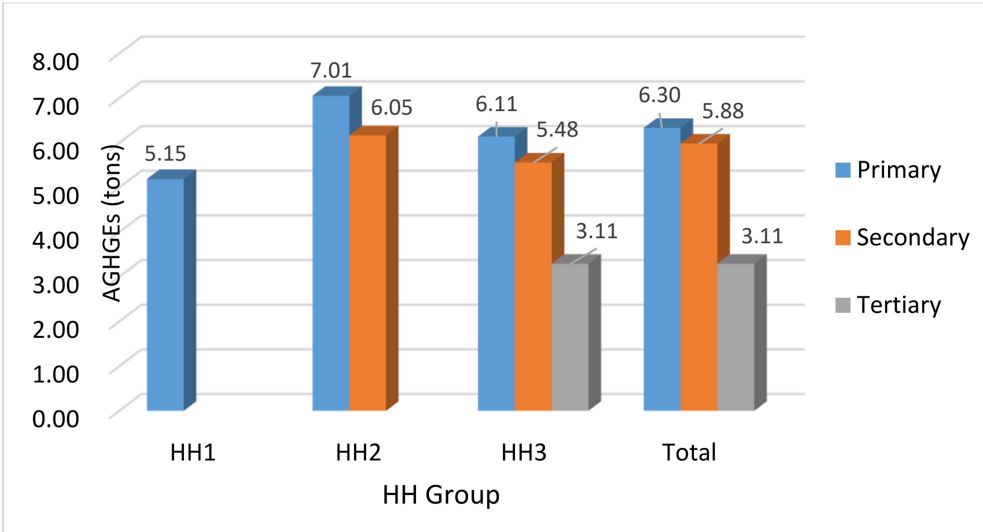


Fig. 4. Annual GHGEs for households' primary, secondary, and tertiary vehicles.

Fig. 4 shows the average annual GHGEs for households' primary, secondary, and tertiary vehicles. We can observe that the primary vehicles produce the highest emissions because they are used most frequently. On the contrary, the tertiary vehicles produce the lowest emissions because they are not frequently in use. For households with one vehicle, the average annual GHG emission is 5.15 tons which is consistent with the 2013 annual report from the EPA. On average, the annual GHGEs for households' primary, secondary, and tertiary vehicles are 6.30 tons, 5.88 tons and 3.11 tons respectively.

Policy Analysis

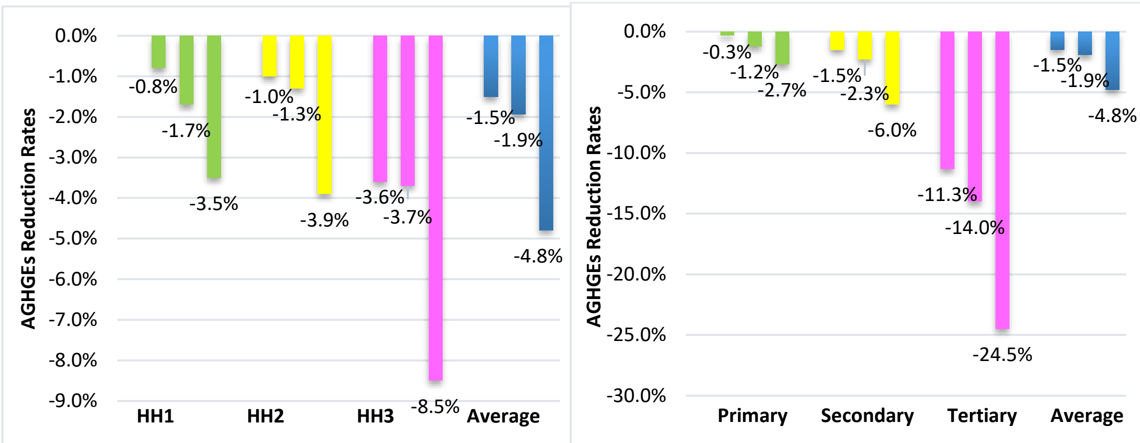
In the US, three main vehicle-related taxes are applied during different stages of a vehicle lifetime: purchase tax, ownership tax and fuel tax (Hayashi et al., 2001). In this section, we propose three policy plans to test and compare impacts of reducing vehicle GHGEs from the three vehicle-related taxes. For comparison purpose, equivalent increments of $92.5, $185, and $370 additional annual fee are considered for the three plans respectively (Liu and Cirillo, 2015). Table 5 shows the specification of the three policy plans based on data provided by the 2009 NHTS.

Table 5
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%

Sensitivity Analysis for Purchase Tax

Purchase tax is a tax on vehicle purchase price. In the three policy plans, the proposed purchase tax is equivalent to an additional charge of 10%, 20%, and 40% of the current vehicle price. Purchase tax is expected to reduce the number of vehicles within households. Fig. 5 shows annual GHGEs reduction rates under the three purchase tax plans.



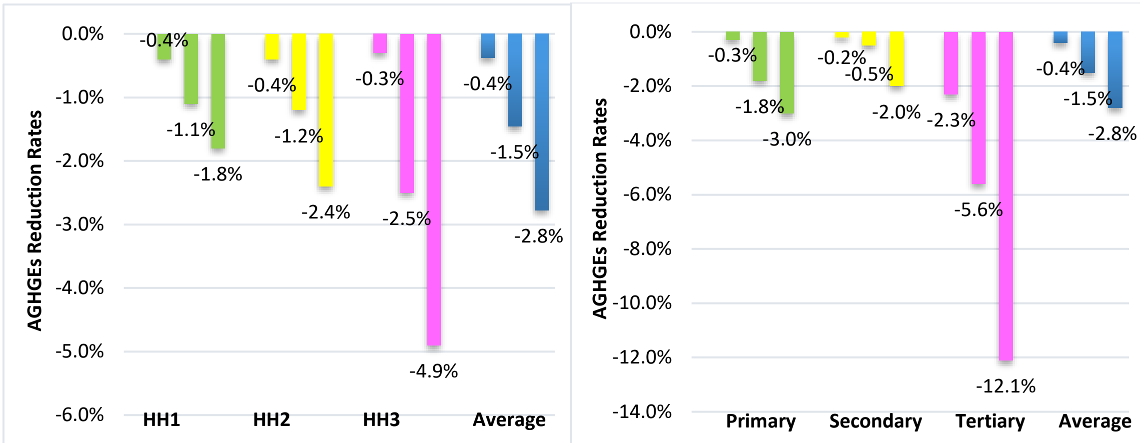
(A) (B)

Fig. 5. Annual GHGEs reduction rates under purchase tax.

Fig. 5 (A) presents the annual GHGEs reduction rates for households with one, two, and three vehicles under the three policy plans. We can observe that the purchase tax reduces annual vehicle GHGEs under all three plans and it is more effective in reducing emissions from households with more vehicles. Fig. 5 (B) illustrates GHGEs reduction rates for households' primary, secondary, and tertiary vehicles. Correspondingly, we can observe purchase tax mainly reduce emissions for tertiary vehicles. For households with one and two vehicles, the reduction rates are small which indicates that these groups hold the number of vehicles that satisfies their basic travel demands. On average, the implementation of the three policy plans reduces households' annual GHGEs by 1.5%, 1.9%, and 4.8%.

Sensitivity Analysis for Ownership Tax

Ownership tax is an annual fee for each vehicle. In the three policy plans, we propose an additional annual charge of $92.5, $185, and $370 per vehicle, subtracting from households' income. Fig. 6 shows annual GHGEs reduction rates under the three ownership tax plans.



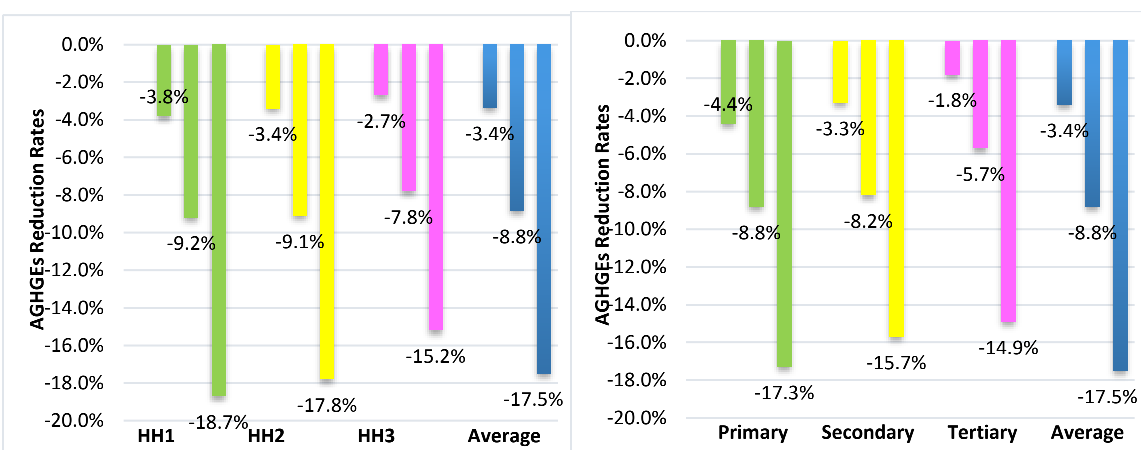
(A) (B)

Fig. 6. Annual GHGEs reduction rates under ownership tax.

As expected, ownership tax is able to reduce vehicle GHGEs under all three policy plans. Although ownership tax is not as effective to reduce emissions as purchase tax, it also has higher impact for households with more vehicles. In addition, ownership tax mainly reduces emissions for households' tertiary vehicles. On average, the implementation of the three policy plans reduces households' annual GHGEs by 0.4%, 1.5%, and 2.8%.

Sensitivity Analysis for Fuel Tax

Fuel tax is a tax on gas consumption. In the three policy plans, the proposed fuel tax is equivalent to an additional charge of 5%, 10%, and 20% of the gas price. Fuel tax is expected to decrease households' vehicle usage for the study area. Fig. 7 shows annual GHGEs reduction rates under the three fuel tax plans.



(A) (B)

Fig. 7. Annual GHGEs reduction rates under fuel tax.

From Fig. 7 (A), we can observe that fuel tax reduces vehicle GHGEs for households with one, two, and three vehicles under all three policy plans. Different from purchase tax and ownership tax, fuel tax is more effective in reducing emissions for households with fewer vehicles. Besides, fuel tax has higher impact on emission reductions for vehicles used more frequently, as illustrated by Fig. 7 (B). The average households' annual GHGEs reduction rates under the three policy plans are 3.4%, 8.8%, and 17.5%.

Conclusions

The proposed model system is designed to forecast vehicle GHGEs and to evaluate effects of vehicle-related taxation schemes on private vehicle GHGEs. The model system integrates four sub-models: (a) vehicle type and vintage choice; (b) vehicle quantity choice; (c) vehicle usage choice; and (d) vehicle GHGEs rates estimator. The vehicle quantity model accounts for type/vintage preferences by incorporating the mode of the type/vintage sub-model. 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. The vehicle quantity probit model and the vehicle usage regression models are combined by an unrestricted full variance covariance matrix, which considers the interdependence between households' discrete and continuous choices. The model framework integrates with MOVES2014 which calculates emission rates for different vehicle types.

Using MOVES2014, we estimate the average GHGEs rates for the Washington D.C. Metropolitan Area. Both start/extended idle emission rates look-up tables and running emission rates look-up tables are developed.

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

The coefficients estimated by the integrated discrete-continuous car ownership model are significant, yielding a generally good correspondence to the observed situation. The vehicle GHGEs rates calculated by MOVES2014 and the vehicle GHGEs predicted by the integrated model system are consistent with EPA's annual report.

The impact of three vehicle-related taxation policies to reduce GHGEs are evaluated and compared. Three policy plans are proposed considering a series of equivalent increments of \$92.5, \$185, and \$370 annual fee per vehicle. The results indicate that: (a) Fuel tax is the most effective in reducing GHGEs compared to ownership tax and purchase tax under different tax rates; (b) Fuel tax has higher impact on emission reduction for households with fewer vehicles. This tax mainly reduces GHGEs by decreasing households' vehicle usage, especially for the low-income group; (c) Ownership taxes have the lowest impact on GHGEs reduction among the three different types of taxes. It reduces GHGEs by decreasing both households' vehicle quantity and usage; (d) Purchase taxes have higher impact for households with more vehicles. It mainly reduces GHGEs by decreasing households' vehicle quantity.

The conceptual framework developed is general and can be applied to other zones and counties. The model can be further expanded for application to state and national geographical level. Moreover, the inclusion of other variable types in the model makes it possible to test different taxation policies, and to support decisions aiming at reducing the vehicle emission footprint.

Acknowledgments

This material is based upon work supported by the National Science Foundation under Grant N. 1131535. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Appendix A

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 Sub-model	HH socio-demographic Land use	Income Number of drivers HH head gender Residential density Vehicle type logsum	Estimated HH vehicle 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

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