Model System to Evaluate Impacts of Vehicle Purchase Tax and Fuel Tax on Household Greenhouse Gas Emissions

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This paper proposes a model system to forecast household-level greenhouse gas emissions (GHGEs) from private transportation and evaluate the effects of car-related taxation schemes on vehicle emissions. The system contains four submodels that specifically capture households' vehicle and vintage, quantity, usage, and GHGE rates (GHGERs) by vehicle type. The vehicle GHGERs are calculated with the Motor Vehicle Emission Simulator 2014, which is authorized by the Environmental Protection Agency. The whole model system was applied to the Washington, D.C., metropolitan area. The 2009 National Household Travel Survey was employed with supplementary data from Consumer Reports, American Fact Finder, and 2009 state motor vehicle registrations. The study proposed two tax schemes, vehicle purchase tax and fuel tax, and predicted their effects on reductions in vehicle GHGEs. The average annual GHGE per vehicle was 5.86 tons of carbon dioxide–equivalent gas without the proposed taxes. After two taxation policies were implemented, the results showed the following: (*a*) the impacts on reducing GHGEs from fuel taxes were higher than those from purchase taxes, (*b*) purchase taxes reduced GHGEs mainly by decreasing the number of cars of households with more vehicles, and (*c*) fuel taxes successfully reduced GHGEs by decreasing the use of cars by households with fewer vehicles. The model system can be extended to other zones, counties, states, and nations.

The increase in mobility demand and motorization rates has caused unsustainable levels of congestion and pollution worldwide. Energy consumption and pollutant emissions from the transportation sector have increased significantly in recent decades. In the United States, according to United Nations Framework Convention on Climate Change's annual report, 27% of the total greenhouse gas emissions (GHGEs) were from the transportation sector in 2011. Within the transportation sector, light-duty vehicles were by far the largest pollutant sources, accounting for 61% of the total GHGEs (*1*). Given the important role of private transportation, it is urgent to apply effective, innovative, and quantitative methodologies to support public authority decision making and analyze the impacts of taxation policies on the reduction of GHGEs (*2*).

Car ownership models that capture households' vehicle miles traveled (VMT) can be used to study problems deriving from traffic congestion, excessive fuel consumption, and high pollutant emission rates (*3*). In addition, car ownership models are necessary to estimate energy demand, fuel prices, and the inventory of carbon dioxide (CO_2) emissions (*4*). Therefore, public agencies and private organizations are interested in employing car ownership models for policy analysis (*2*). For instance, the U.S. Department of Energy, state departments of transportation, auto industries, and the World Bank have supported studies on car ownership models and used their results for policy analysis (*5*). For GHGEs, this type of model system is adopted to examine the life cycle of CO_2 emissions from automobile transport and the tax revenues associated with different taxation policies (*6*). National governments use car ownership models to forecast tax revenues and the regulatory impact under different taxation policies (*6–8*).

For private vehicles, a tax to reduce GHGEs can encourage drivers to (*a*) buy a newer or cleaner car; (*b*) buy a smaller, fuel efficient car; (*c*) repair their broken pollution control equipment; (*d*) use cleaner gasoline; (*e*) drive less; (*f*) drive less aggressively; and (*g*) avoid cold start-ups (*9*). Hayashi et al. (*6*) determined the effects of varying the weights of the tax components according to changes in car type and vintage mix, car users' driving patterns, and behaviors in Japan.

This study proposed a general model system to forecast household-level vehicle GHGEs and evaluate the effects of car-related taxation schemes on GHGEs. A specific car ownership model was included in the system to capture vehicle type and vintage, quantity, and usage, which are necessary to obtain household-level GHGEs. The motor vehicle emission simulator (MOVES), authorized by the Environmental Protection Agency (EPA), was adopted to estimate GHGE rates (GHGERs) for different types of vehicles. The effects from purchase tax and fuel tax to reduce household-level vehicle GHGEs have been predicted and compared.

The next section of the paper is a literature review on car ownership models and methods to estimate GHGEs. The following section presents the model system, which includes the following four submodels: (*a*) vehicle type, (*b*) vehicle quantity, (*c*) vehicle usage, and (*d*) vehicle emission rates. The model system was applied to the Washington, D.C., metropolitan area. Three taxation plans were proposed to reduce household-level GHGEs. A comparison of the effects of a purchase tax and a usage tax is presented to identify feasible taxation policies. Finally, the paper presents the summary and avenues for future research.

LITERATURE REVIEW

Car Ownership Models

Disaggregate discrete choice models in the form of multinomial or ordered logit have been proposed to forecast household vehicle holding. Models have been estimated for different countries, including

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the United Kingdom (*10*), the Netherlands (*11, 12*), Norway (*13*), Australia (*14*), and the United States (*15, 16*).

The joint decision of owning one car or multiple cars and driving a certain number of miles has been modeled with discrete-continuous models. The earliest generation of discrete-continuous models was derived from the conditional indirect utility function, based on microeconomic theory (*14, 15, 17–20*). In 1984, Dubin and McFadden (*21*) and Hanemann (*22*) were the first to develop an integrated discrete-continuous model that estimated car ownership and car usage. They assumed that households chose the combination of number of cars and VMT with the highest utility. In 2005, Bhat developed multiple discrete-continuous extreme value models that jointly estimated households' vehicle type, quantity, and VMT (*23*). This type of model was applied to analyze the impacts of demographics, built environment attributes, vehicle characteristics, and gasoline prices on household vehicle holding and usage (*24, 25*). The advantages of the multiple discrete-continuous extreme value model are (*a*) the modeling framework is consistent with the random utility theory, (*b*) it captures trade-offs among the usage of different types of vehicles, and (*c*) it accommodates a large number of vehicle classifications. Vehicle holding and usage were also studied by Fang (*26*), who proposed a Bayesian multivariate ordered probit and Tobit model. In this model system, an ordered probit model determines households' decisions on vehicle quantity corresponding to two categories (cars and trucks). The multivariate Tobit model was applied to estimate household decisions on VMT. Overall, the model was well suited for predicting changes in the number of vehicles and miles traveled for each vehicle type (*26*).

Estimation of GHGEs and Taxation Policies

In recent years, several emissions estimation models have been proposed: for instance, California's EMFAC7F (emissions factors software), EPA's MOBILE5a (vehicle emissions modeling software), and EPA's MOVES model (*27*). According to the EPA, two methods can be used to calculate GHGEs: one is from vehicle GHGERs and the other is from fuel consumption. The first approach has become popular since the development of the MOVES software, which efficiently estimates GHGERs for different vehicle types. The second approach is more traditional and estimates GHGEs by determining the CO_2 production rate from gasoline and gasoline consumption (*28*). From *Emission Facts* by the EPA, the key steps for calculating GHGEs for a private vehicle are (*a*) determining the CO_2 produced per gallon of gasoline; (*b*) estimating the fuel economy (mpg) of passenger cars or light-duty trucks; (*c*) determining the VMT; (*d*) determining the components of greenhouse gas, including CO_2, methane (CH_4), nitrous oxide (N_2O), and hydrofluorocarbons; (*e*) estimating the relative percentages of passenger cars and light-duty trucks; and (*f*) calculating annual GHGEs (*28*).

On the policy side, a significant number of research works in different disciplines have explored market incentives that could be considered to reduce emissions (*29*). Dargay and Gately applied the car ownership model to forecast the growth of household vehicle quantity to the year 2015 for the Organisation for Economic Co-operation and Development countries, and estimated the growth in energy demand and emissions (*4*). 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. Davis and Kilian (*30*) pointed out that studies on the adoption of a carbon tax often fail to address two important problems: (*a*) the endogeneity of gasoline prices and (*b*) the responsiveness of gasoline consumption to a change in tax, which may differ from the responsiveness to a change in average price. Their models successfully overcame these challenges with 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 emissions by about 1.5% in the United States (*30*). In 2001, Hayashi et al. (*6*) proposed a model system that specifically determined the effects of different components of taxation policies at the stages of car purchase, car ownership, and car usage. The model system was applied to analyze the impact of the 1989 tax reform in Japan and to forecast future reductions in GHGEs under different taxation schemes.

MODEL SYSTEM

The proposed model system is illustrated in Figure 1. A car ownership model, which contains three submodels, was employed to estimate household vehicle type, quantity, and usage, which served as inputs for the vehicle GHGERs calculation. In the vehicle GHGERs submodel, MOVES was used to estimate emission rates for households' different types of gasoline-using vehicles. In Figure 1, HH represents household, yellow color represents inputs, blue color represents submodels, and red color represents outputs.

Table 1 highlights the input and output parameters used in the four submodels. Vehicle characteristics, household sociodemographics, and land use variables are the main attributes of the model system. Table 1 shows annual VMT (AVMT).

Vehicle Type Submodel

The vehicle type submodel is designed to forecast households' preferences on different vehicle types and vintages. Two possible vehicle types were considered, passenger cars and passenger trucks, and three vintages, model year from 2006 to 2009 (not older than 3 years), model year from 2003 to 2005 (between 3 and 6 years old), and model year before 2003 (older than 6 years). Table 2 illustrates how the different vehicle classifications in the 2009 National Household Travel Survey (NHTS) were adapted to MOVES. A series of multinomial logit models was employed to determine the preferences on vehicle types and vintages for households holding different numbers of vehicles. One-vehicle households can choose from six alternatives; two-vehicle households can choose among 6×6 different combinations of alternatives, and three-vehicle households have a choice set composed of $6 \times 6 \times 6$ alternatives.

A qualitative analysis of the data collected in the Washington, D.C., metropolitan area shows that only 8% of the households have no private vehicles (HH0). Of the households with one vehicle (HH1), most prefer passenger cars (70%) to trucks (30%). For households with two (HH2) or three (HH3) vehicles, there is no obvious preference for passenger cars or trucks (see Figure 2*a*). In addition, around half of the vehicles in the sample are older than six years.

Vehicle Quantity Submodel

The methodology for forecasting households' vehicle quantity was derived from Train (*17*), Cirillo and Liu (*31*), and Liu et al. (*2*). It basically combines a vehicle type model and a quantity model by assuming that a household chooses vehicle type and vintage conditional on the number of vehicles the household holds. The vehicle quantity

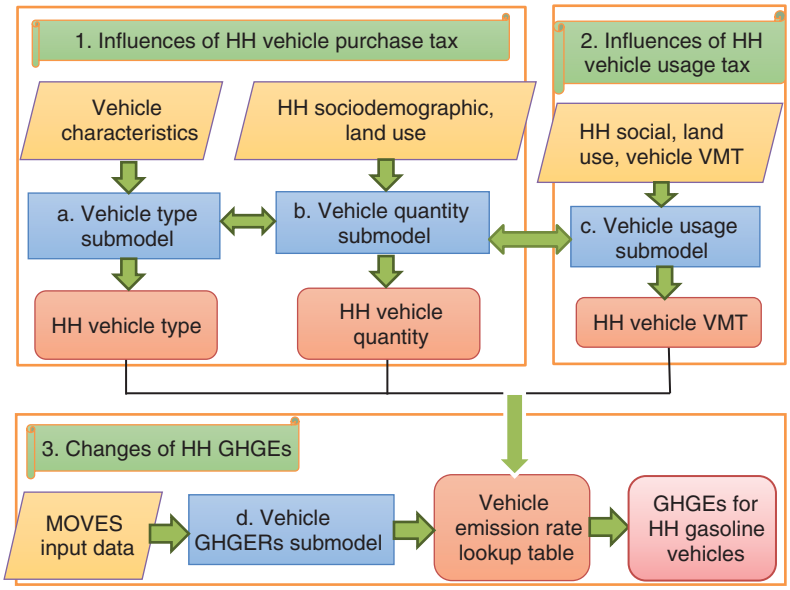

FIGURE 1 Structure of model system (HH = household).

TABLE 1 Submodel Inputs and Outputs

	Input		
Submodel	Variable Type	Parameters	Output
Vehicle type	Vehicle characteristics	Purchase price Shoulder room Luggage capacity Average MPG	Estimated vehicle type
Vehicle quantity	HH sociodemographic Land use	Income Number of drivers HH head gender Vehicle type log sum Urban size Residential density	Estimated HH vehicle quantity
Vehicle usage	Vehicle VMT and cost HH sociodemographic Land use	Income HH head gender Own home or not Residential density Travel cost	Estimated vehicle AVMT
Vehicle emission rate	Vehicle characteristics 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 Vehicle annual GHGEs HH annual GHGEs

NOTE: AVMT = annual vehicle miles traveled.

TABLE 2 Vehicle Type Mapping Between NHTS and MOVES

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	Recreational vehicle	31	Passenger truck
08	Golf cart	31	Passenger truck

submodel is a multinomial probit model with four alternatives; the submodel includes households with 0, 1, 2, and 3 vehicles. The submodel considers mainly household sociodemographics and land use attribute variables:

$$U_N = V_N + \lambda V_{t_k|N} + \varepsilon_N \qquad N = 0, 1, 2, 3 \tag{1}$$

where

U_N = household's actual (indirect) utility of holding N vehicles,
V_N = utility of holding N vehicles,
$V_{t_k|N}$ = utility of choosing vehicle type and vintage t_k conditional on holding N vehicles, and
ε_N = error term, which follows a standard normal distribution.

In Equation 1, the conditional utility $V_{t_k|N}$, can be rewritten as the log sum of the vehicle type model:

$$L = \ln \sum_{t_k} \exp\left(V_{t_k}\right) \tag{2}$$

where the number of alternatives in t_k varies depending on the number of cars owned by the household.

The distribution of households by number of vehicles in the Washington, D.C., metropolitan area is shown in Figure 2*b*. Almost half the households in this area have two vehicles and the average number of vehicles per household is 1.91, which is in line with the national average.

Vehicle Usage Submodel

For the usage submodel, a linear regression was adopted to forecast the annual VMT of each household vehicle, considering attributes such as households' sociodemographics, land use variables, and the cost of driving. The general formula for the regression can be written as follows:

$$Y_{\text{reg}} = X_{\text{reg}}^T \beta_{\text{reg}} + \varepsilon_{\text{reg}} \qquad \varepsilon_{\text{reg}} \sim N\left(0, \sigma^2\right) \tag{3}$$

where

Y_{reg} = linear combination of a vector of predictors X_{reg} and the multivariate normal error term ε_{reg},
β_{reg} = vector of coefficients corresponding to predictors X_{reg}, and
T = transpose.

Three regressions were employed to estimate the AVMT of households' primary, secondary, and tertiary vehicles. An instrumental variable approach was used to avoid endogeneity (*17*). Figure 2*c* shows the relationship between households' size and number of workers, drivers, and AVMT. As the number of workers and drivers increases with household size, AVMT increases correspondingly.

Vehicle GHGERs Submodel

The vehicle GHGERs submodel is the core part of the GHGE estimator. MOVES was adopted to estimate GHGERs for different vehicle types during the start, extended idle, and running processes. MOVES estimates emissions of CO_2, CH_4, and N_2O, which are the main components of greenhouse gas. An emissions rate lookup table can be built when transforming GHGERs into CO_2 equivalents (CO_2e).

Several assumptions were made: (*a*) annual GHGERs are the average emission rates during a typical summer month and a typical winter month; (*b*) vehicle age is an integer and is the difference between the current year (2009 for NHTS data) and the vehicle model year; (*c*) only gasoline vehicles were considered, excluding electric, hybrid, and diesel vehicles; (*d*) GHGERs of the Washington, D.C., metropolitan area are the average GHGERs of one low-density county,

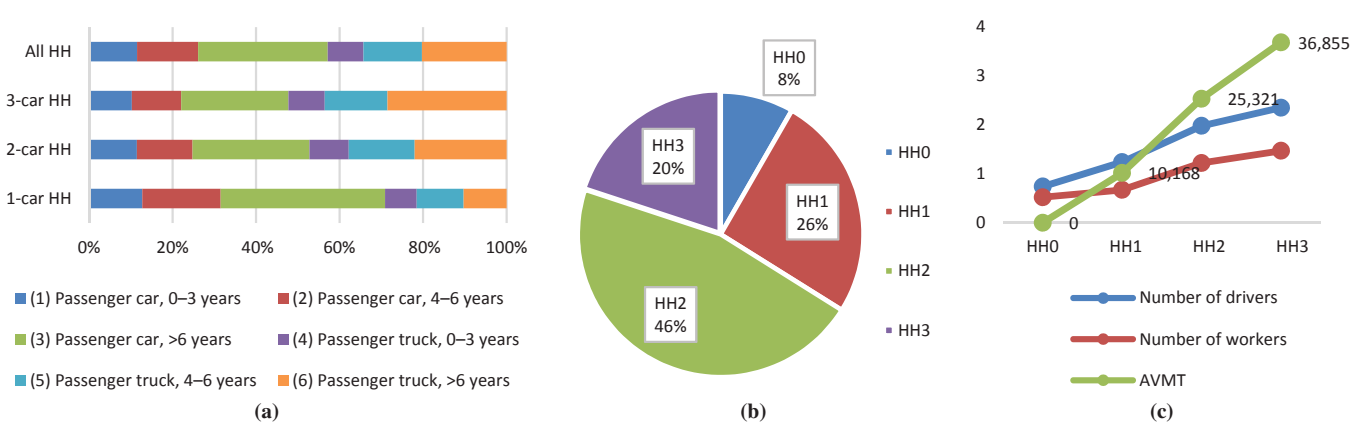

FIGURE 2 Distribution of vehicle type, quantity, and usage in Washington, D.C., metropolitan area: (*a*) distribution of household cars and trucks by vehicle age, (*b*) distribution of households by number of vehicles, and (*c*) household number of drivers, number of workers, and AVMT by number of household vehicles.

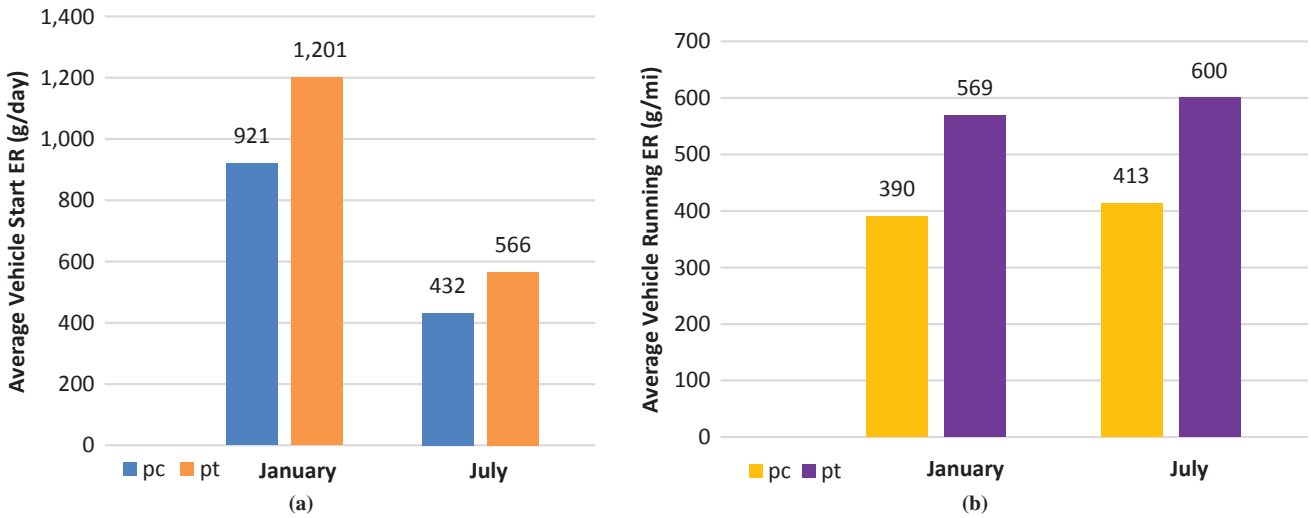

FIGURE 3 Average vehicle emission rates: (*a*) start and extended idle and (*b*) running (ER = emission rate; pc = passenger car; pt = passenger truck).

one mid-density county, and one high-density county; (*e*) only weekdays were considered; (*f*) it was assumed that the number of vehicles traveling in a county equals the number of registered vehicles of that county; and (*g*) the share of hydrofluorocarbons was assumed to be 3%, according to the EPA.

In MOVES, a run specification and the input database are necessary to describe a target zone and its traffic conditions. The run specification contains the 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 three states—Maryland, Virginia, and West Virginia—and the District of Columbia, encompassing 18 counties. Thus, the county-level scale was selected for the run specification. To forecast GHGEs for each household in the target area, emission rates should be chosen instead of inventory. For time spans, two scenarios were selected: a typical summer month, July 2009, and a typical winter month, January 2009. The study focused on the following pollutants: CO_2, CH_4, and N_2O; their emission rates were transformed into CO_2e.

The input database, which corresponds to the run specification, contains 10 data files: (*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. The source types considered were passenger cars and passenger trucks, which are the main types of vehicles held by households in the Washington, D.C., metropolitan area. The data were mainly derived from 2009 state motor vehicle registrations from FHWA, the 2009 NHTS, and MOVES default data.

The output database, mainly including rate per vehicle and rate per distance, provides vehicle start and extended idle emission rates (g/vehicle) and running emission rates (g/vehicle/mi) for the selected pollutants. According to the estimated vehicle type submodel, household vehicles are classified into six categories based on size and vintage. Therefore, for each category, the emission rates can be calculated by obtaining the weighted average of the speed bins, road types, and temperatures. Figure 3*a* compares the start and extended idle and Figure 3*b* compares the running emission rates between July and January for the Washington, D.C., metropolitan area. For comparison purposes, the emission rates of all the pollutants were transformed into CO_2E.

From Figure 3, it is obvious that passenger trucks generate higher GHGEs than passenger cars during the start and extended idle and running processes. Moreover, the start and extended idle emission rates in January were more than twice those in July, which is reasonable because of the longer start time and more fuel consumption in the winter. In the running process, the emission rates in January were slightly lower than those in July; this is consistent with what has been found in experimental settings (*32, 33*). McMichael and Sigsby (*32*) showed that in the running process after the completion of the cold-start, CO_2 emissions under winter conditions are slightly lower than under summer conditions. Tables 3 and 4 show the start and

TABLE 3 Average Start and Extended Idle Emission Rates Lookup Table

	Passenger Car				Passenger Truck			
Age	CH_4	N_2O	CO_2	CO_2e	CH_4	N_2O	CO_2	CO_2e
0–3	0.280	0.214	605.113	677.185	0.397	0.290	786.046	884.202
4–6	0.333	0.214	605.115	678.293	0.527	0.294	784.166	886.487
>6	0.141	0.214	605.113	674.267	0.308	0.288	784.068	879.697

NOTE: Age in years; emission values in g/vehicle/day.

TABLE 4 Average Running Emission Rates Lookup Table

	Passenger Car				Passenger Truck			
Age	CH_4	N_2O	CO_2	CO_2e	CH_4	N_2O	CO_2	CO_2e
0–3	0.004	0.008	399.109	401.647	0.004	0.020	577.547	583.674
4–6	0.004	0.008	399.224	401.770	0.009	0.021	577.763	584.304
>6	0.004	0.008	399.340	401.893	0.008	0.020	579.010	585.320

NOTE: Age in years; emission values in g/vehicle/day.

extended idle and running emission rates in the Washington, D.C., metropolitan area. The results show a lack of vehicle age sensitivity in the estimation of the vehicle emission rates.

With the information on households' vehicle type, quantity, usage, and GHGERs from the discrete-continuous model, it is possible to calculate annual GHGEs for each household vehicle. The annual GHGEs for each vehicle can be calculated by the following formula:

$$\text{AGHGEs (grams)} = \text{RERs}\left(\frac{\text{grams}}{\text{vehicle mile}}\right) * \text{AVMT} + \text{SERs} * \left(\frac{\text{grams}}{\text{vehicle day}}\right) * 365\left(\frac{\text{days}}{\text{year}}\right) \quad (4)$$

where AGHGEs is annual greenhouse gas emissions, and RERs and SERs represent running emission rates and start and extended idle emission rates, respectively. Figure 4 compares the average vehicle AGHGEs over households with one, two, and three vehicles. For households with one vehicle, the average AGHGE is about 5.2 tons; higher emission rates are calculated for households with more than one vehicle. HH0, HH1, HH2, and HH3 represent households with zero, one, two, and three vehicles, respectively.

POLICY ANALYSIS FOR WASHINGTON, D.C., METROPOLITAN AREA

The model system was applied to the Washington, D.C., metropolitan area to estimate (*a*) change in car ownership shares, (*b*) change in car usage, and (*c*) change in households' annual GHGEs under different tax policies. In developed countries, there are three main 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, the United Kingdom, Germany, and Japan, the weights among the tax components vary (*6*). In the United States, about 80% of car-related taxes are purchase and fuel taxes. Therefore, the analysis focused on purchase tax and fuel tax.

From the 2009 NHTS data for the Washington, D.C., metropolitan area, average AVMT, average travel cost, and average purchase price were calculated. The baseline values for the analysis were: (*a*) average AVMT per vehicle, 12,021 mi; (*b*) average travel cost per vehicle per mile, $0.154; and (*c*) average current price per vehicle, $9,315. The analysis assumed that the average vehicle life was 10 years and ignored inflation.

For comparison purposes, the analysis considered equivalent increments of $92.5, $185, and $370 in additional annual fees for the three plans considered. Table 5 shows how the three plans affect the current purchase price and fuel price.

Sensitivity Analysis for Purchase Tax

For the purchase tax, an additional charge of $92.5, $185, and $370 in annual fee per vehicle per year was applied, which is equivalent to increases of 10%, 20%, and 40%, respectively, in the purchase price over one year. These plans were expected to reduce the number of vehicles owned by residents in the study area, especially for groups with more vehicles. The scenarios are summarized as follows:

Policy 0. Keep the current tax rates,

Policy 1. Increase the purchase tax by 10% of the current vehicle price,

Policy 2. Increase the purchase tax by 20% of the current vehicle price, and

Policy 3. Increase the purchase tax by 40% of the current vehicle price.

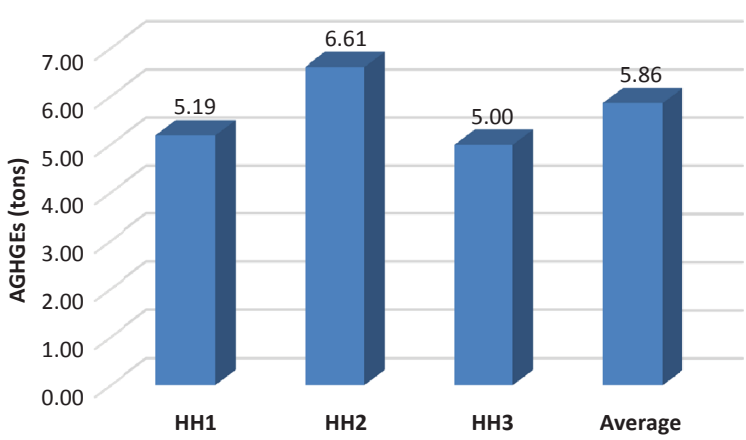

FIGURE 4 Average vehicle AGHGEs by number of household vehicles.

TABLE 5 Taxation Plans

Equivalent Increment	Policy Plan Number	Purchase Tax (%)	Usage (fuel) Tax (%)
$92.5/car and year	1	+10	+5
$185/car and year	2	+20	+10
$370/car and year	3	+40	+20

The shares of car ownership under the three taxation policies are presented in Figure 5*a*. The annual reduction in GHGE rates under the three taxation policies are shown in Figure 5*b*.

As expected, the shares of households with two or three vehicles decreased, while the shares of households with zero or one vehicle increased under the three policies. As the majority of American families are heavily dependent on cars, the increasing or decreasing rates become smaller although the tax rates increase faster. Figure 5*b* presents the annual GHGE reduction rates for households with one, two, and three vehicles under the three policies. All three purchase taxes reduce annual GHGEs. For households with one or two vehicles, the reduction rates are small, which indicates that these groups hold the number of vehicles that satisfy their basic travel and vehicle demands. In contrast, the purchase taxes make a significant impact on households with three vehicles. On average, the implementation of the three policies will reduce the households' annual GHGEs by 5%, 6%, and 9%, respectively.

Sensitivity Analysis for Fuel Tax

The fuel tax foresees an additional charge of $92.5, $185, and $370 per vehicle per year, which is equivalent to an average increase of 5%, 10%, and 20%, respectively, of the travel fee (fuel cost/mi). The usage plans are expected to reduce vehicle usage and will mainly affect low-income households. The scenarios are presented as follows:

Policy 0. Keep the current tax rates,
Policy 1. Increase fuel price 5%,
Policy 2. Increase fuel price 10%, and
Policy 3. Increase fuel price 20%.

The changes in vehicle AVMT for different household groups under the three taxation policies are presented in Figure 6*a*. The figure shows that AVMT decreases under the three fuel taxation policies for all households. Figure 6*b* reports the annual reduction in GHGEs for all household groups under the three taxation policies.

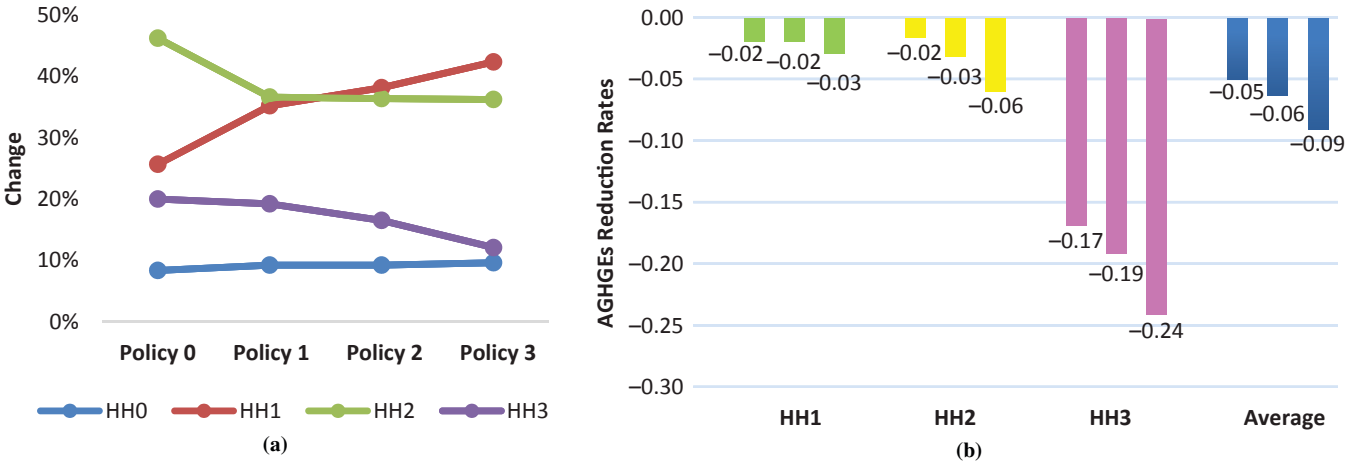

FIGURE 5 Purchase tax results: (*a*) change in vehicle ownership shares and (*b*) GHGE reduction.

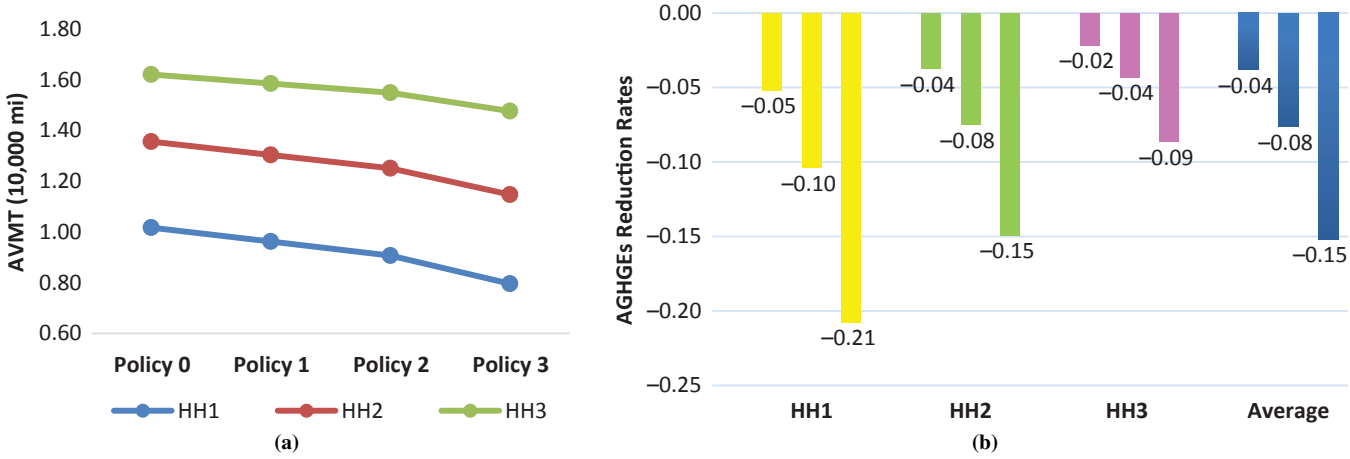

FIGURE 6 Usage tax results: (*a*) change in vehicle AVMT and (*b*) GHGE reduction.

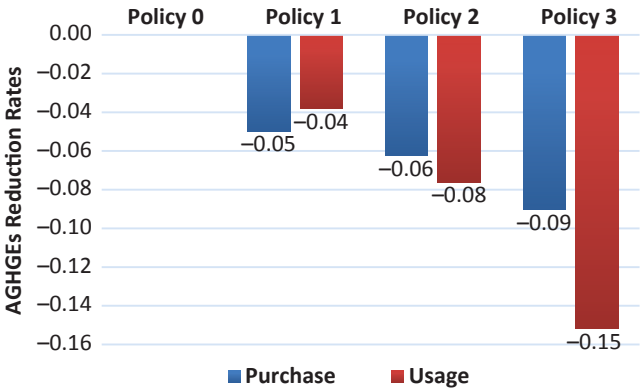

FIGURE 7 Comparison of effects of purchase tax and usage tax.

The reduced annual GHGE rates are higher for households with fewer vehicles. On average, the implementation of the three policies will reduce households' annual GHGEs by 4%, 8%, and 15%, respectively.

Comparison Between Purchase Tax and Fuel Tax

Figure 7 compares the effects of purchase taxes and fuel taxes on households' annual GHGEs under the three taxation plans. Although the impact of the purchase tax on reducing annual GHGEs is higher under Policy 1, the impact of fuel tax increases is much faster. The annual reduction in GHGEs is higher when the fuel tax is applied under Policies 2 and 3.

CONCLUSION

This study proposed a model system to forecast vehicle GHGEs and evaluate the effects of car-related taxation schemes on household-level vehicle GHGEs. The model system is composed of four submodels: (*a*) vehicle type and vintage choice, (*b*) vehicle quantity choice, (*c*) vehicle usage submodel, and (*d*) vehicle GHGERs submodel. A discrete-continuous car ownership model was successfully applied to calculate households' vehicle ownership, type, and usage behaviors, and employed MOVES to estimate GHGERs for different types of vehicles. Consequently, the household-level vehicle GHGEs were calculated.

The attributes considered in the model system were car characteristics, household sociodemographic characteristics, land use variables, vehicle driving cost, and county traffic condition variables. The model was estimated with the 2009 NHTS and supplementary data sets from Consumer Reports, the 2009 state motor vehicle registration provided by FHWA, and MOVES default data.

The model system was 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 submodels were significant, yielding a generally good correspondence to the observed situation. Vehicle GHGERs calculated by MOVES were slightly overestimated according to the assumptions.

Sensitivity analysis was conducted based on a series of equivalent increments of $92.5, $185, and $370 annual fee per vehicle. The effects of the purchase taxation policies and fuel taxation policies on household-level GHGEs were tested. There were three main results. First, fuel taxes are more effective in reducing GHGEs than purchase taxes at higher tax rates. Second, purchase taxes have higher impacts for households with more vehicles. These policies mainly reduce GHGEs by decreasing households' car quantity. Third, fuel taxes have higher impacts for households with fewer vehicles. The policies mainly reduce GHGEs by decreasing households' car usage.

Currently, the model system is being further expanded for possible application to other zones, counties, states, and nations. The conceptual framework of the model system is general and can be used to investigate other taxation policies.

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