UNIVERSITY OF MARYLAND

The present and the future of car ownership in the US

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Workshop

“Autos, People and Policies (APPs):

Addressing the Issues of the New Millennium”

University of Maryland

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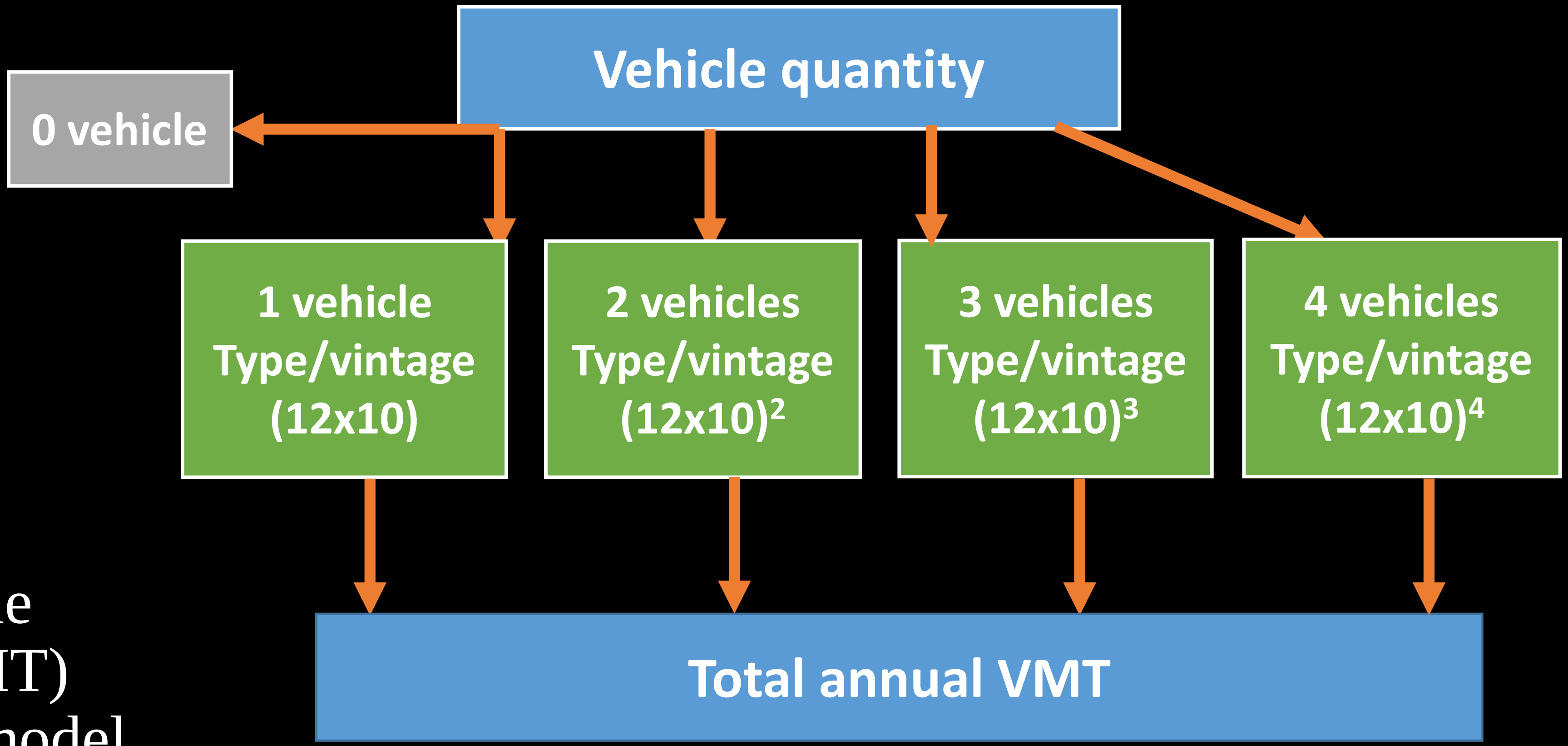
The Present

- Based on real data (mainly the 2008 National Household Travel Survey) we have estimated:
- The number of vehicle per household in the Washington Metropolitan area.
- The type and vintage of the vehicle in the household
- The total mileage travelled and the miles travelled with each vehicle
- We have extended the model to the 4 Regions of the USA and three area types (urbanized area, urban clusters and rural)
- Estimated the effect of improved transit service on vehicle ownership and use.
- Calculate the GHGEs from the integrated model above.

Integrated Discrete-Continuous Car Ownership Model (Liu et al., 2013)

- ➢Vehicle quantity choices
  MNP
- ➢Vehicle type and vintage choices
  MNL
- ➢Total annual vehicle miles traveled (VMT)
  Linear regression model



Data Sources

- The 2009 National Household Travel Survey (NHTS)

  i.e. Household (HH) social demographic, land use, vehicle ownership, VMT, driving cost

- The Consumer Reports

  i.e. vehicle characteristics

- The American Fact Finder

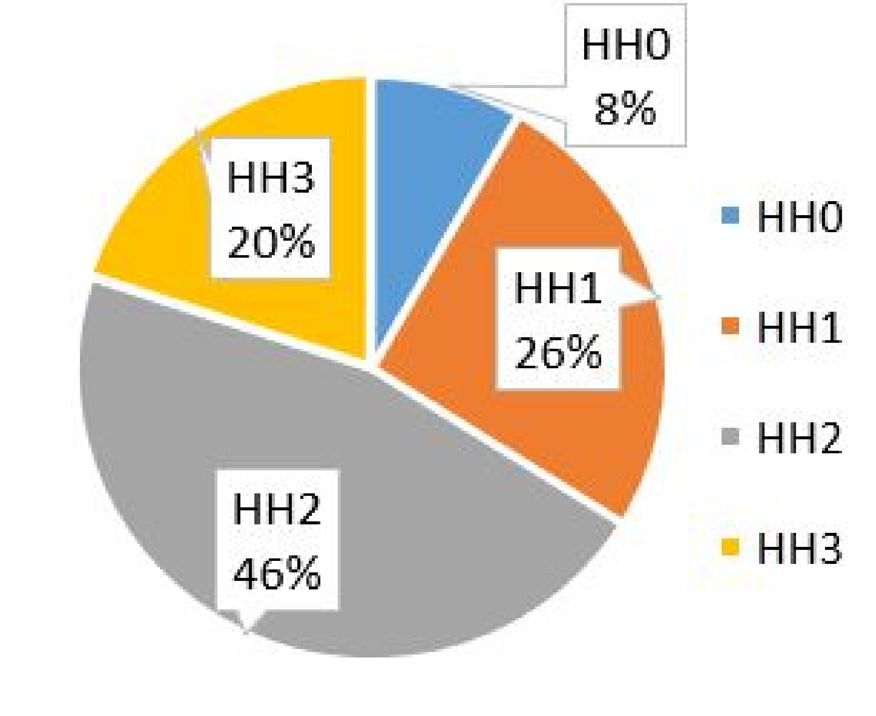
  i.e. residential population

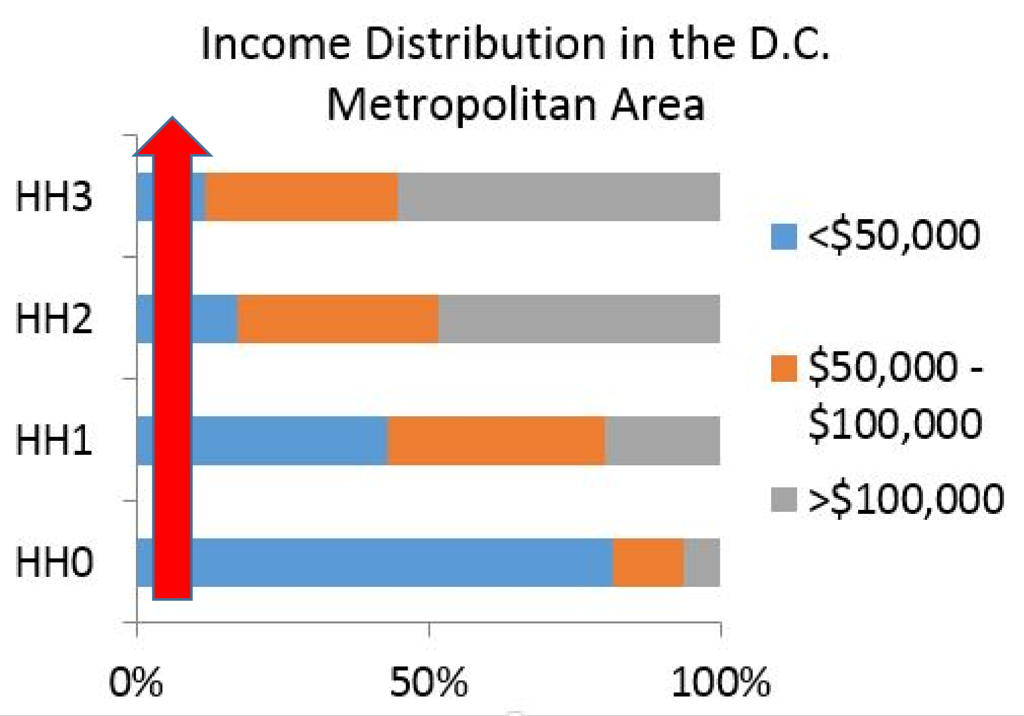
- The 2009 State Motor Vehicle Registrations (SMVR)

  i.e. vehicle population

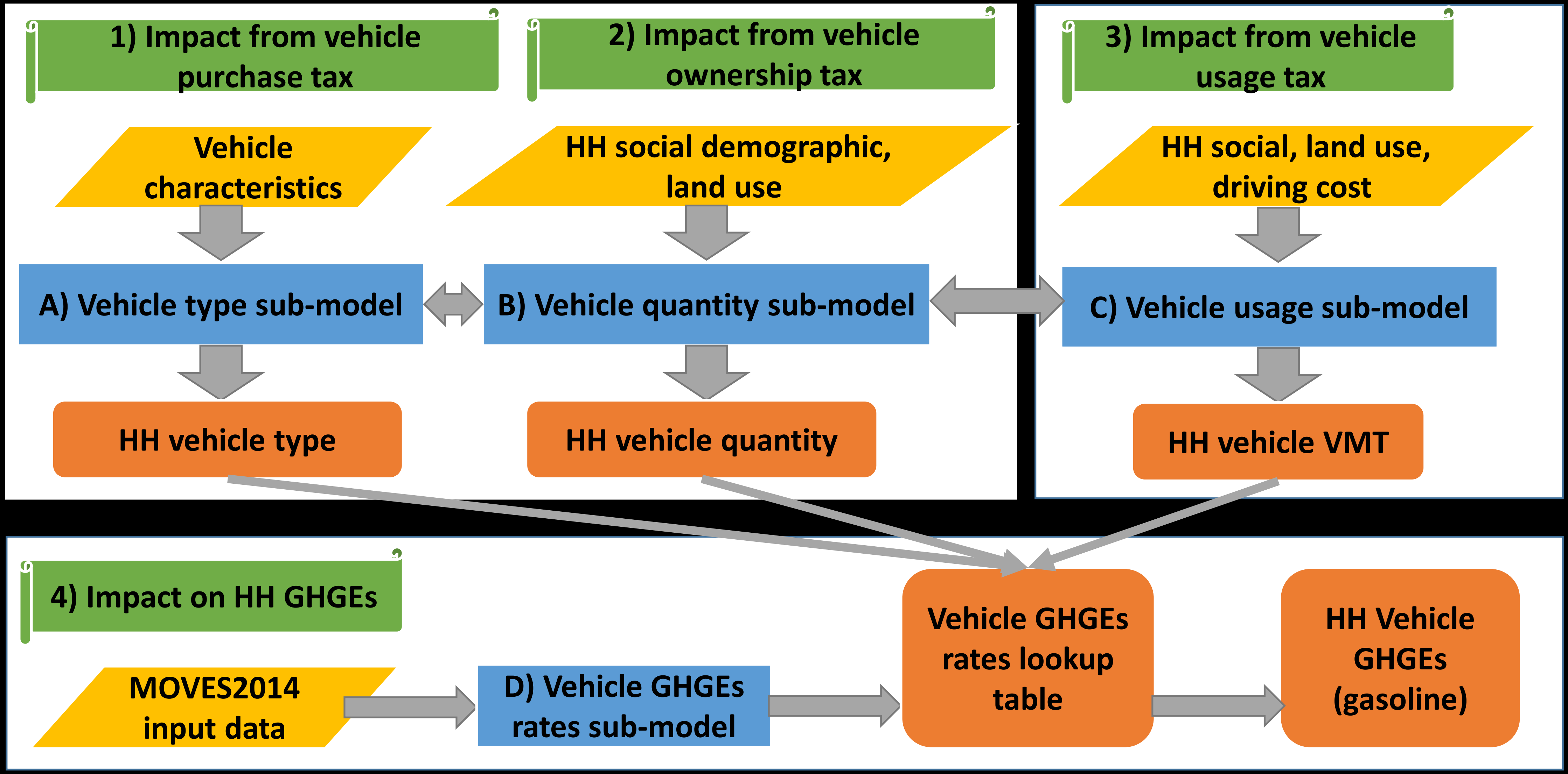
- MOVES Default Database

Descriptive Statistics of the 2009 NHTS in the Washington D.C. Metropolitan Area





Structure of the Proposed Model System



Vehicle Type Sub-Model

- MNL model
- Data sources: the *Consumer Reports* and the 2009 NHTS
- Number of alternatives: 6 for HH1, 6x6 for HH2, 6x6x6 for HH3

  2 types: passenger car / passenger truck

  3 vintages: 2006-2009 / 2003-2005 / pre-2002
- Number of attributes: 6

  Car characteristics

  - purchase price ($1000)
  - shoulder room (in.)
  - luggage capacity (cu. ft.)
  - average MPG
  - number of make/model in this class
  - dummy at least one new car in the HH

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	

Vehicle Quantity Sub-Model

- MNP model
- Alternatives: HH0, HH1, HH2, HH3
- Attributes: Social-demographic and land use variables
- Utility function: $U_{N,i} = V_{N,i} + \alpha L_{N,i} + \varepsilon_{N,i} \quad , \varepsilon_{N,i} \sim_{iid} N(0, \mathbf{\Sigma})$

  $U_{N,i}$: Indirect utility of household i holding N vehicles

  $V_{N,i}$: Deterministic utility of household i holding N vehicles

  $L_{N,i}$: The expected maximum utility of choosing vehicle type for household i holding N vehicles

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

- Probability of choosing type t'_N: $P_{t'_N|N} = \frac{\exp(V_{t'_N|N})}{\sum_{j=1}^{t_N} \exp(V_{j|N})}$

Vehicle Usage Sub-Model

- Linear regression models

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

$Y_{reg,s}$: Annual vehicle miles traveled (VMT) for the primary, secondary and tertiary vehicles holding by households

$X_{reg,s}$: Explanatory variables such as income and fuel cost

- A general regression model

$$Y_{reg} = X_{reg}^T \beta_{reg} + \varepsilon_{reg} \ , \qquad \varepsilon_{reg} \sim MVN(0, \mathbf{\Sigma}_{reg})$$

$$\text{where } \mathbf{\Sigma}_{reg} = \begin{bmatrix} \sigma_{reg,1st}^2 & \sigma_{reg,1st,2nd} & \sigma_{reg,1st,3rd} \\ \sigma_{reg,2nd,1st} & \sigma_{reg,2nd}^2 & \sigma_{reg,2nd,3rd} \\ \sigma_{reg,3rd,1st} & \sigma_{reg,3rd,2nd} & \sigma_{reg,3rd}^2 \end{bmatrix}$$

- The likelihood of observing Y_{reg}

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

Integrated Discrete-Continuous Model

- Joint probability of vehicle quantity and usage (Liu et al. 2013)

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

- Probability of observing Y_{reg}

$$\mathrm{P}(Y_{reg}) = \varphi(\varepsilon_{reg} | \mu = \mathbf{0},\ \Sigma = \Sigma_{reg}),\quad \varepsilon_{reg} = Y_{reg} - \widehat{Y_{reg}}$$

- $(Y_{disc} \mid Y_{reg})$ follows a conditional multivariate normal distribution (Liu et al. 2013)

$$\text{If} \begin{bmatrix} A \\ B \end{bmatrix} \sim MVN(\mu, \Sigma) \text{ where } \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}$$

$$\text{Then } (A|B) \sim MVN(\mu_{A|B}, \Sigma_{A|B}) \text{ where } \mu_{A|B} = \mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(B - \mu_2),$$

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

- Integrated error term

$$(\tilde{\varepsilon}_1, \tilde{\varepsilon}_2, \tilde{\varepsilon}_3, \widetilde{\varepsilon_{reg,n}}) \sim MVN(\mathbf{0}, \Sigma_{3+n}),\ \Sigma_{3+n} = \begin{bmatrix} \Sigma_{disc} & \Sigma_{disc,reg} \\ \Sigma_{reg,disc} & \Sigma_{reg} \end{bmatrix}$$

Estimation Results of Integrated Model (Vehicle Quantity Part)

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

Estimation Results of Integrated Model (Vehicle Quantity Part)

Num. of drivers	1 car	1.103	0.043	<0.001
	2 cars	2.942	-	-
	3 cars	3.953	-	-
HH head gender (1 for Male)	1 car	0.759	0.054	<0.001
	2 cars	1.262	-	-
	3 cars	1.360	-	-
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	-	-
	3 cars	-0.630	0.055	<0.001

Estimation Results of Integrated Model (Vehicle VMT Part)

Constant	Regression for primary vehicle	5.014	0.123	<0.001
Income		0.050	0.007	<0.001
HH head gender		0.243	-	-
Res. density		-0.052	0.009	<0.001
Driving cost		-2.983	0.057	<0.001
Constant	Regression for secondary vehicle	5.088	-	-
Income		0.023	-	-
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 third vehicle	5.190	-	-
Income		0.014	-	-
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	-3852.398			
Log-likelihood at convergence	-2982.707			
Number of observations	1289			

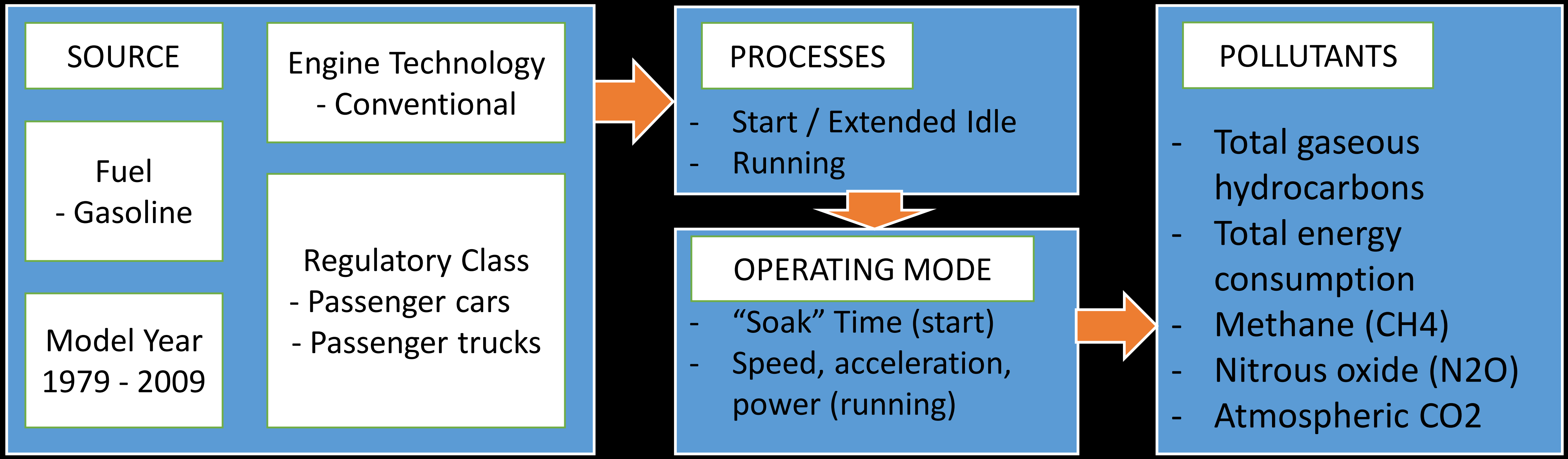
Model Validation

Re-estimate the model on 80% of the households and predict by applying the estimated coefficients on the rest 20% of the households.

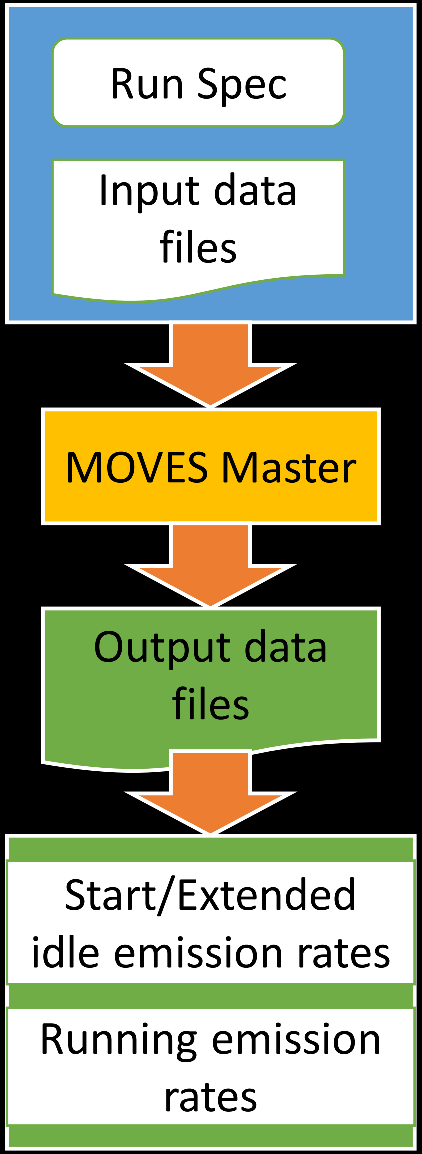
		Actual	Forecast	Difference
Car Ownership	0-car household	10.9%	13.2%	2.3%
	1-car household	22.6%	22.6%	0.0%
	2-car household	45.5%	44.7%	-0.8%
	3-car household	21.1%	19.5%	-1.5%
	Average car ownership	1.77	1.71	-3.4%
AAVMT (average annual vehicle miles traveled)	Primary car mileage	11753.3	11960.7	1.8%
	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%

GHGEs Rates Sub-Model - MOVES

- MOVES2014, is an emission modeling system which estimates emissions for mobile sources covering a broad range of pollutants and allows multiple scale analysis.
- Main components of GHGs are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydro-fluorocarbon (HFC)



GHGEs Rates Sub-Model - MOVES



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

GHGEs Rates Sub-Model – Cluster Analysis

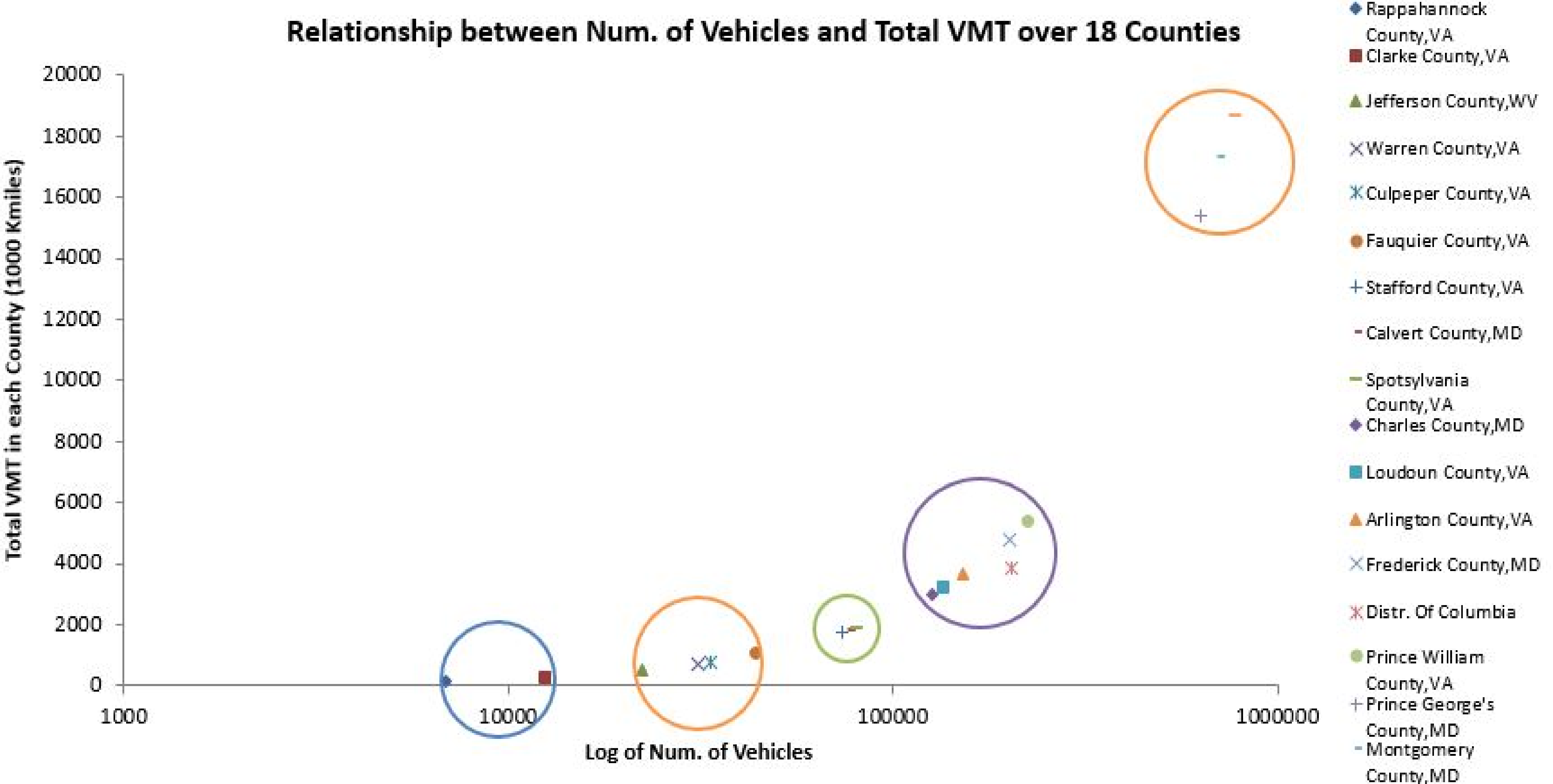
18 Counties in
- Maryland
- Virginia
- West Virginia
- Distr. of Columbia

MOVES Run Spec
- County-Level

Cluster Analysis
- Vehicle population
- Total VMT

Group ID	Counties	Representative County	Vehicle share of the group
1	Rappahannock, VA	Rappahannock, VA	0.5%
	Clarke, VA		
2	Warren, VA	Jefferson, WV	3.7%
	Culpeper, VA		
	Jefferson, WV		
	Fauquier, VA		
3	Calvert, MD	Calvert, MD	6.5%
	Spotsylvania, VA		
	Stafford, VA		
4	Charles, MD	Arlington, VA	29.6%
	Loudoun, VA		
	Arlington, VA		
	Frederick, MD		
	Prince William, VA		
	Washington D.C.		
5	Prince George's, MD	Montgomery, MD	59.7%
	Fairfax, VA		
	Montgomery, MD		

GHGEs Rates Sub-Model – Cluster Analysis



GHGEs Rates Sub-Model – Post-Processes

- Rateperdistance (Running)
- Ratepervehicle (Start/Extended idle)

In each scenario:

- one CH_4 rate
- one N_2O rate
- one CO_2 rate

(hourly emission rate)

Rates vary with (num.)	Rateperdistance	Ratepervehicle
Vehicle type (13)	Yes if selected	Yes if selected
Temperature	Yes	Yes
Road type (4)	Yes	--
Speed bin (16)	Yes	--
Type of day (2)	No	Yes
Hour of day (24)	No	Yes
Model year (31)	Yes if selected	Yes if selected
Fuel type (3)	Yes if selected	Yes if selected

GHGEs Rates Sub-Model – Assumptions

(a) Annual GHGE rates are the average of typical summer months (July & August) and typical winter months (January & February)

(b) Only consider gasoline vehicles, no electricity, hybrid or diesel ones

(c) GHGE rates of the Washington D.C. Metropolitan Area are the weighted average of the representative counties decided by the cluster analysis

(d) Only weekday is considered

(e) Assume the number of vehicles traveling in a county equals the number of registered vehicles of that county

GHGEs Rates Sub-Model - Results

Start and Extended Idle Emission Rates for D.C. Metropolitan Area
(grams/vehicle-day)

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

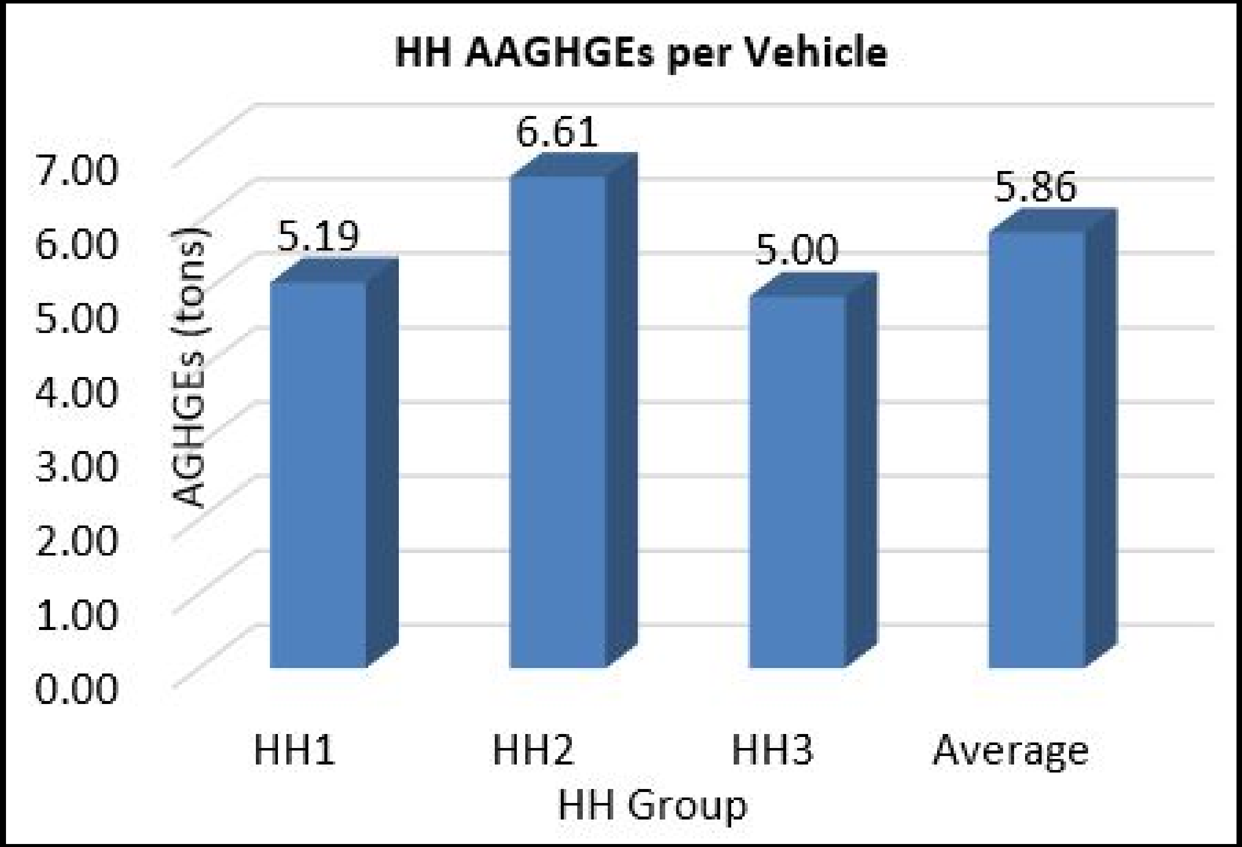
Running Emission Rates for D.C. Metropolitan Area
(grams/vehicle-mile)

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

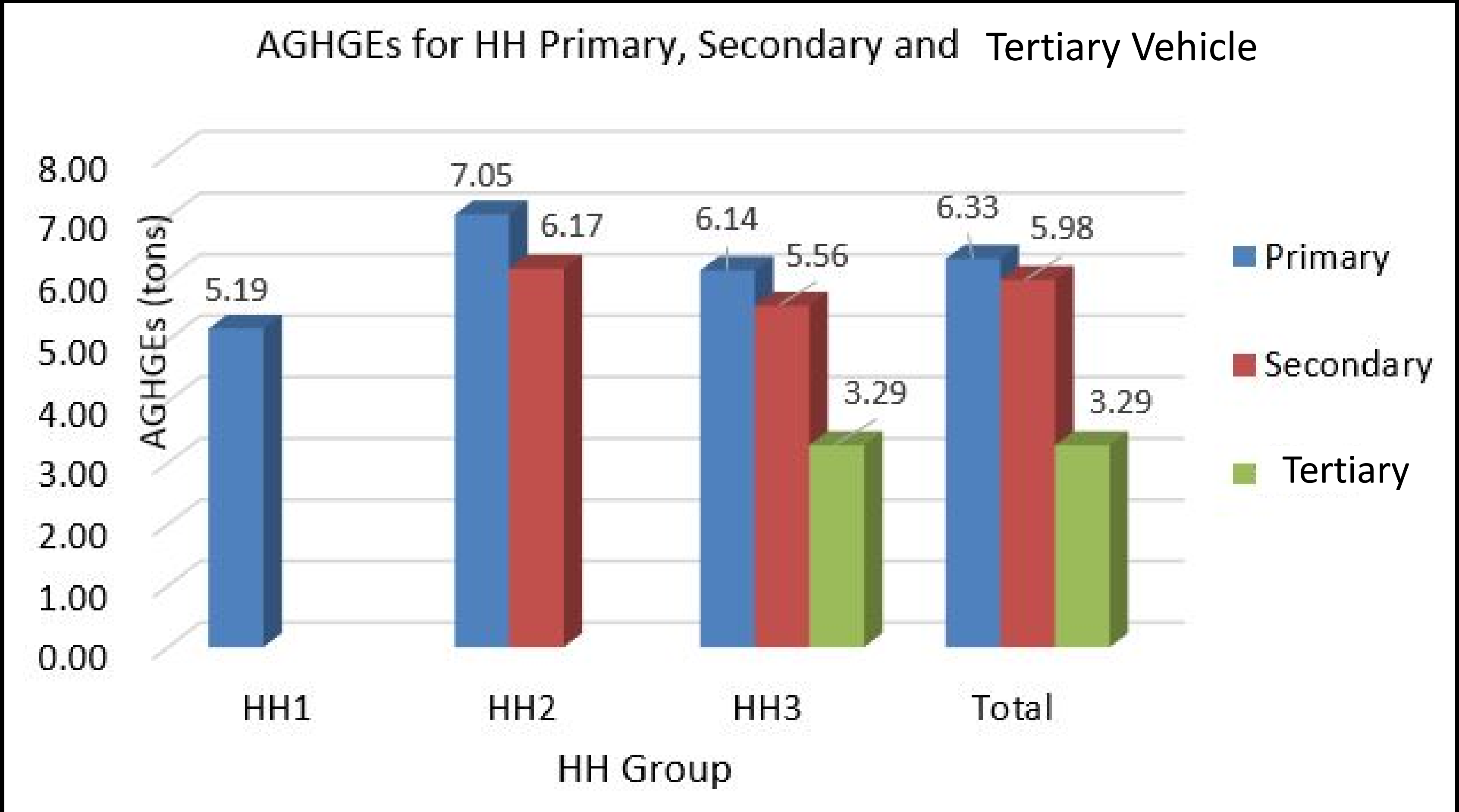
Household-Level Vehicle GHGEs

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

where $RERs$: running emission rates **$SERs$: start and extended emission rates**



Household-Level Vehicle GHGEs

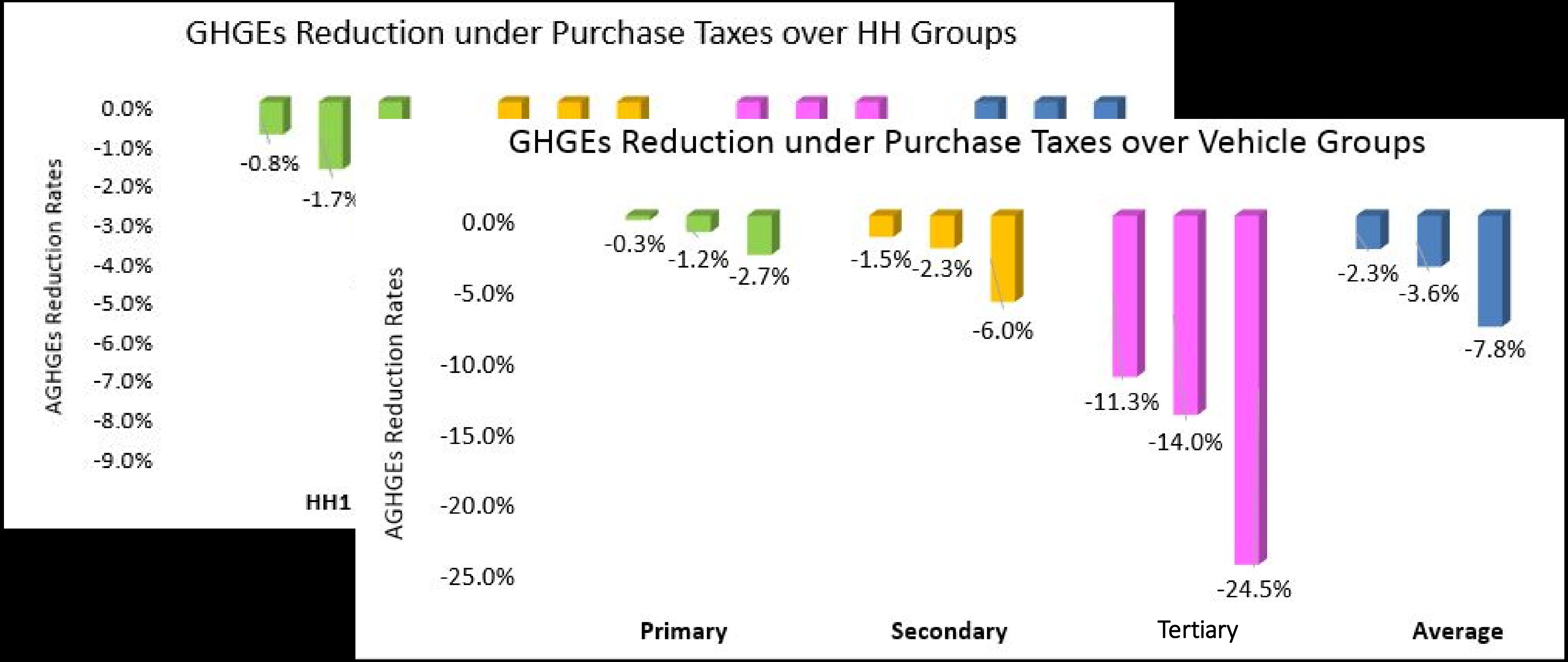


Policy Plan

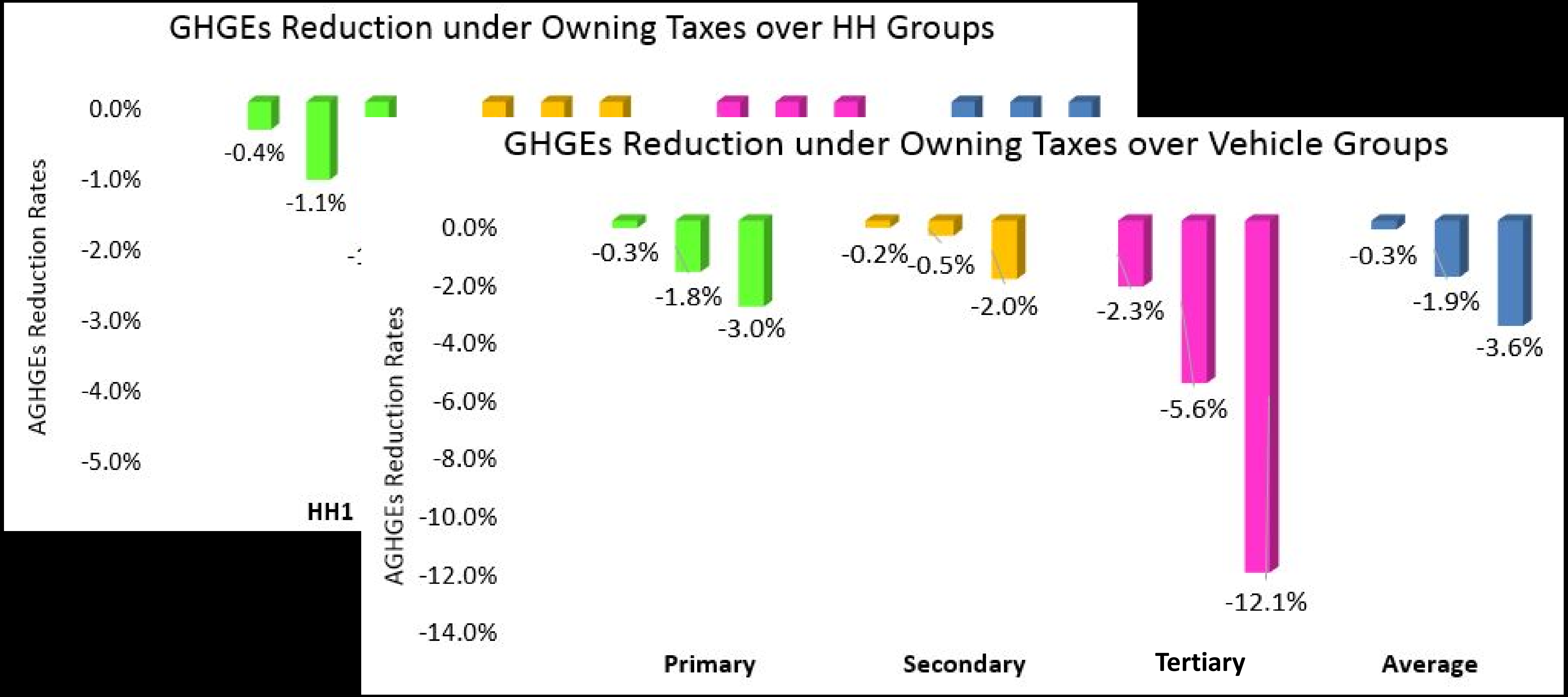
Equivalent increment	Plan ID	Purchase tax	Ownership tax	Fuel tax
$92.5 / car & year	1	+ 10%	$92.5 / car & year	+ 5%
$185 / car & year	2	+ 20%	$185 / car & year	+ 10%
$ 370 / car & year	3	+ 40%	$ 370 / car & year	+ 20%

- Purchase tax: an additional charge to vehicle price
- Ownership tax: a fee charged for each vehicle every year
- Fuel tax: a tax on gas

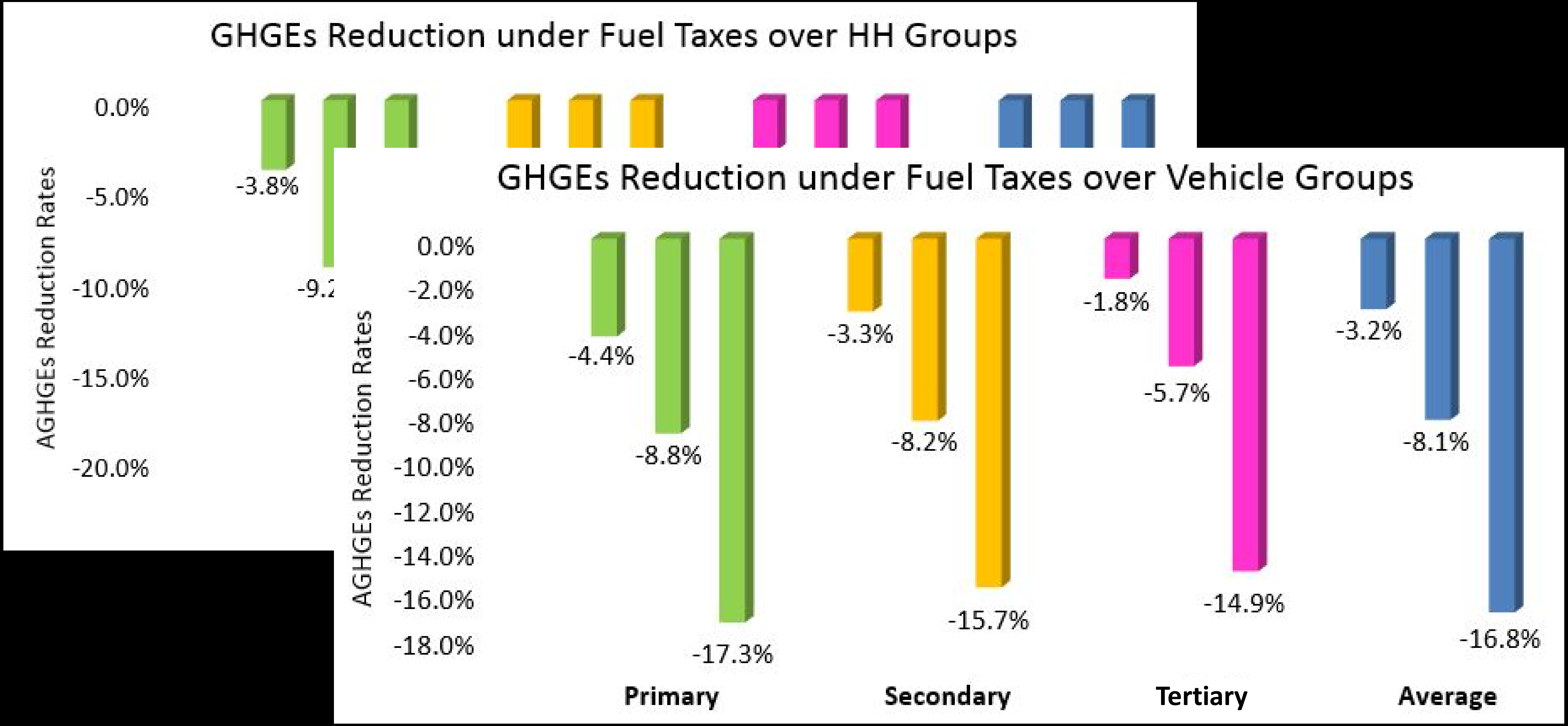
Purchase Taxation Policy



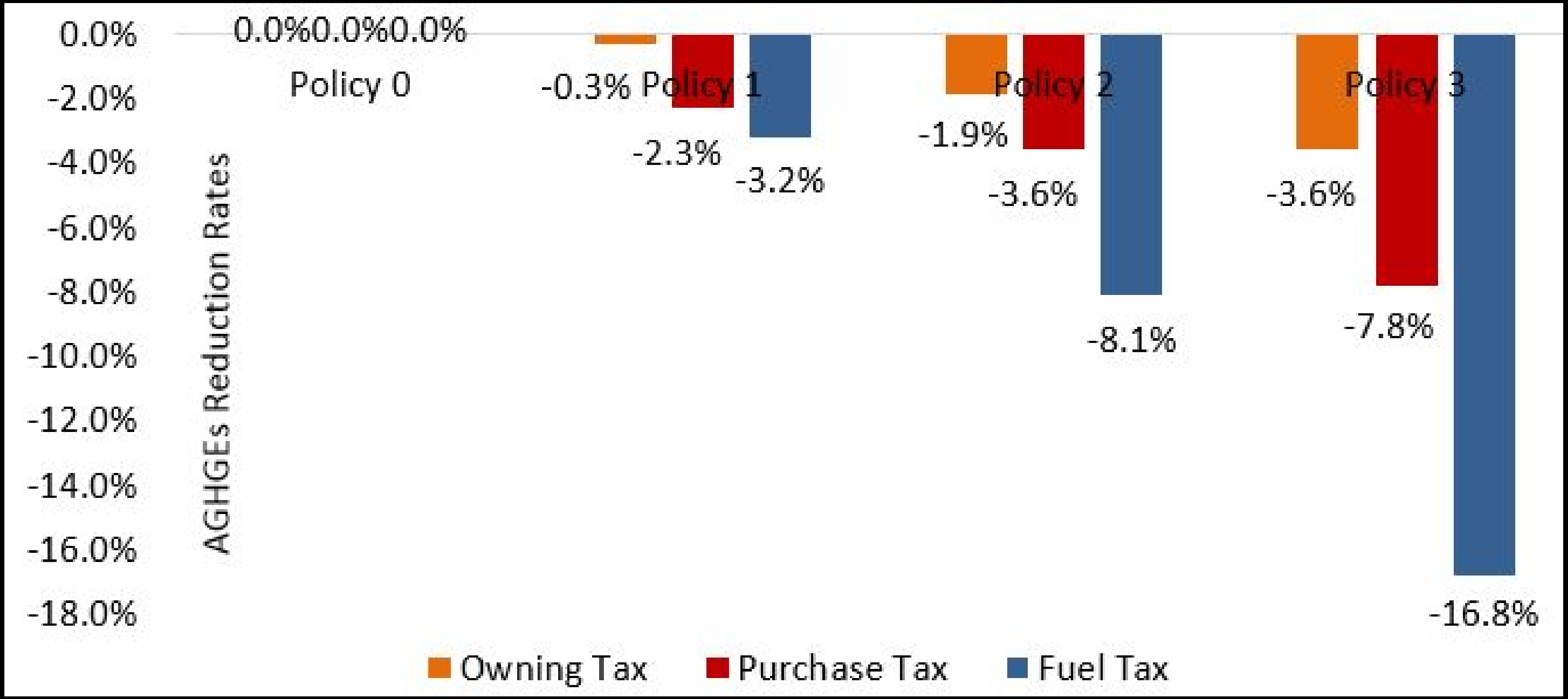
Ownership Taxation Policy



Fuel Taxation Policy



Comparison between Taxation Policies



The Future

Background

- Discrete choice models are commonly used in transportation planning and modeling, but their theoretical basis and applications have been mainly developed in a static context.

- With the continuous and rapid changes in modern societies (i.e. introduction of advanced technologies, aggressive marketing strategies and innovative policies) it is more and more recognized by researchers in various disciplines that choice situations take place in a dynamic environment and that strong interdependencies exist among decisions made at different points in time.

Dynamics models in economics

- Dynamic discrete choice models have been firstly developed in economics and related fields.
- In dynamic discrete choice structural models, agents are forward looking and maximize expected inter-temporal payoffs.
- The consumers get to know the rapidly evolving nature of product attributes within a given period of time and different products are supposed to be available on the market.
- As a result, a consumer can either decide to buy the product or to postpone the purchase at each time period. This dynamic choice behavior has been treated in a series of different research studies.

Review of economics literature

- John Rust (1987) --- bus engine replacement, single agent, two options, one purchase, homogenous attributes of the products, infinite-horizon. Nested Fixed Point method to estimate.
- Oleg Melnikov (2000) --- printer machine demand one purchase, differentiated durable products, homogenous consumers.
- Szabolcs LŐrincz (2005) --- computer servers demand, persistency effects, choice between using the original product and upgrading its format (operating systems). Dynamic nested logit model.
- Juan Esteban Carranza (2006) --- digital camera demand, heterogeneity over consumers' preferences and dynamics of quality.
- Gowrisankaran and Rysman (2007) --- digital camcorder, repeat purchases, heterogeneous consumers and differentiated products.

Model formulation

Dynamic, regenerative, optimal stopping problem

Consumer *i* state at time *t*

$$S_{it} = \{0,1\} \qquad \begin{cases} 0 \text{ if } i \text{ is in the market;} \\ 1 \text{ otherwise.} \end{cases}$$

In each time period consumer *i* in status $S_{it} = 0$ has two options:

(a) to buy one of the products $j \in \Im_t$ or

(b) to postpone

If (a) the consumer *i* obtains a terminal payoff u_{ijt}

If (b) is chosen the consumer obtains a one period payoff c_{it}

One period pay off

$$c(x_{it}, q_{it}; \theta_i, \alpha_i)$$

x_{it}, a vector of attributes for *i* at *t*, e.g. gender, education, professional status, income.

q_{it}, a vector of characteristics of current vehicle owned by *i*, e.g. age, mileage, purchase price, etc.

θ_i, α_i, are parameters for x_{it} and q_{it}.

Terminal payoff

$$u_{ijt} = u\left(x_{it}, d_j, y_{jt}, \theta_i, \gamma_i, \lambda_i, \varepsilon_{ijt}\right)$$

x_{it} **is a vector of static individual attributes** (e.g. age, income, education) and θ_i is the related parameter;

d_j **is a vector of static product attributes** (e.g. vehicle size) and γ_i is the related parameter;

y_{jt} **is a vector of dynamic attributes** (e.g. energy cost per mile, purchase cost, environment incentives), λ_i is the related parameter;

ε_{ijt} **is a random utility** component (i.i.d. GEV)

$$u_{jt} = \delta_{jt} + \varepsilon_{jt}$$

δ_{jt} is the mean utility.

Each time period, the consumer decides to buy or postpone

$$D\left(v_{it}, c_{it}\right) = \max\left\{v_{it}, c_{it} + \beta E\left[D\left(v_{i,t+1}\right)\right]\right\}$$

where: $v_t = \max_{j \in \Im_t} u_{jt}$

Hypothesis:

c_{it} is the payoff when postponing

β is a discount factor (set 1)

$E_t[\cdot] = E[\cdot \mid I_t]$ expected utility

(Based on Bellman equation):

$$D\left(u_{i1t}, \ldots u_{iJt}, c_{it}\right) = \max_{\tau}\left[\sum_{k=t}^{\tau-1} \beta^{k-t} c_{it} + \beta^{\tau-t} E_t \max_{j \in J} u_{ij\tau}\right]$$

where:

τ is time period when consumer decides to buy

Industry evolution

The evolution of the industry is represented by a so called **random walk**; dynamic variable y_{jt} is supposed to follow a normal diffusion process, specified as a random walk with drift η_j

$$\begin{aligned} y_{j,t+1} &= \mu(y_{jt}) + L(y_{jt})\upsilon_{j,t+1} \\ &= \psi_j y_{jt} + \eta_j + L(y_{jt})\upsilon_{j,t+1} \end{aligned}$$

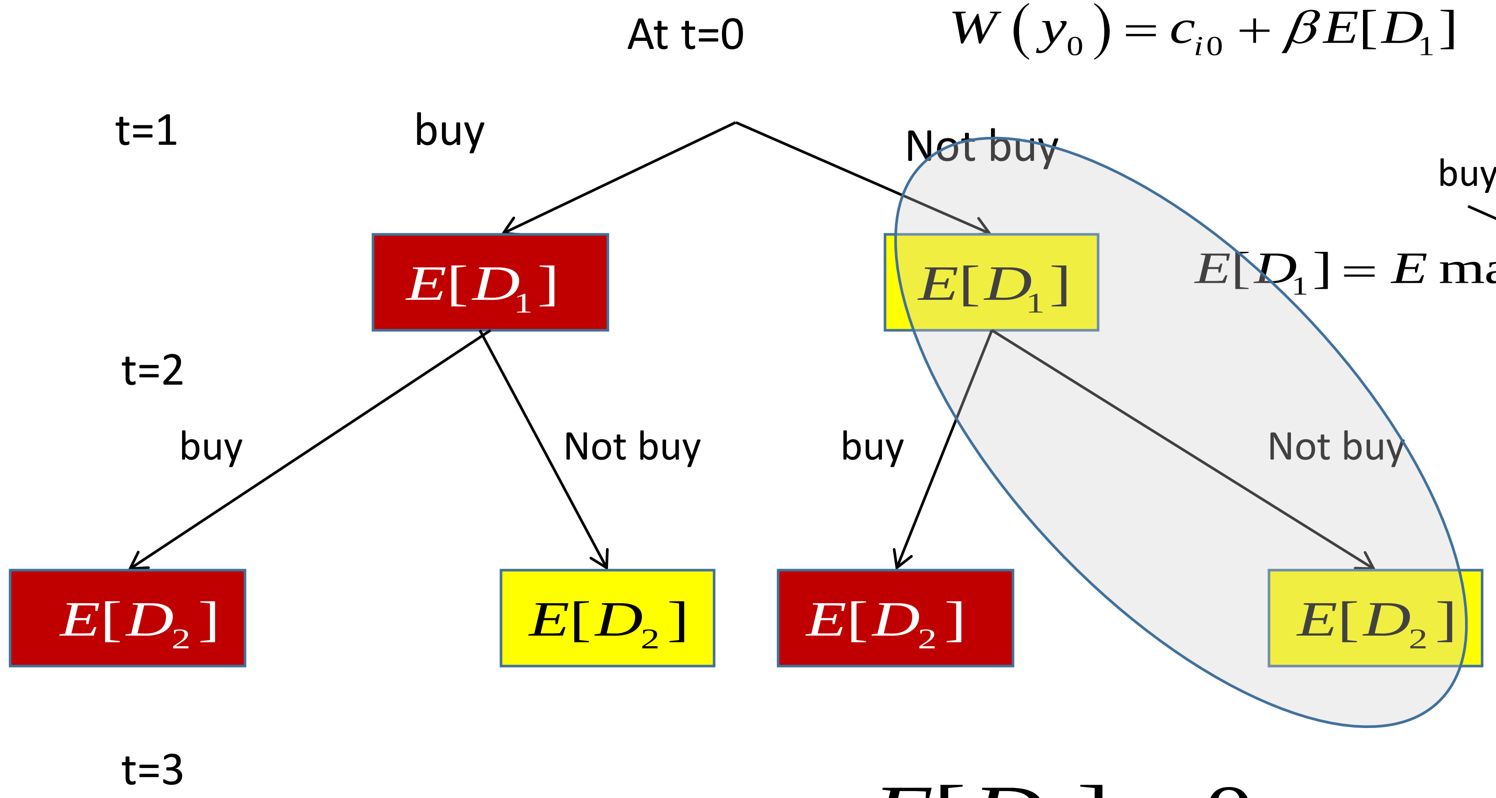
(j=1,…,J, t = 1,…,T) are i.i.d. multivariate standard normal random vectors.

υ_{jt} is the Cholesky factor of the variance-covariance matrix L

$$L(y_{jt})L(y_{jt})^T = \Sigma(y_{jt})$$

Scenario tree

$$W(y_0) = c_{i0} + \beta E[D_1]$$



$$E[D_1] = E\max\{\overset{\text{buy}}{v_{i1}}, \overset{\text{Not buy}}{c_{i1} + E[D_2]}\}$$

$$E[D_2] = E\max\{v_{i2}, c_{i2} + E[D_3]\}$$

$$E[D_3] = 0$$

DDCM applied to carownership

- What effect will the following factors have on the vehicle marketplace over the next five years:
  - New vehicle technology
  - Improvements in existing vehicle technology
  - Greater availability of different energy sources
  - Rising fuel prices
  - Transportation and energy policy

Fuel Type Experiment

Vehicle Ownership in Maryland

A survey about current vehicle characteristics and preferences for future vehicles.

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Question 39.

In 2013, the following fuel characteristics are available:

	Gasoline Fuel	Alternative Fuel	Diesel Fuel	Electricity
Fuel Price, Pre Tax (price per gallon equivalent)	**$5.32**	**$3.29**	**$2.66**	**$5.35**
Fuel Tax	**$0.42**	**$0.30**	**$1.05**	**$0.28**
Fuel Efficiency	**29**	**18**	**40**	**75**
Fueling Station Availability	**Within 5 miles**	**Within 25 miles**	**Within 10 miles**	**5-hr Home Charge Only**

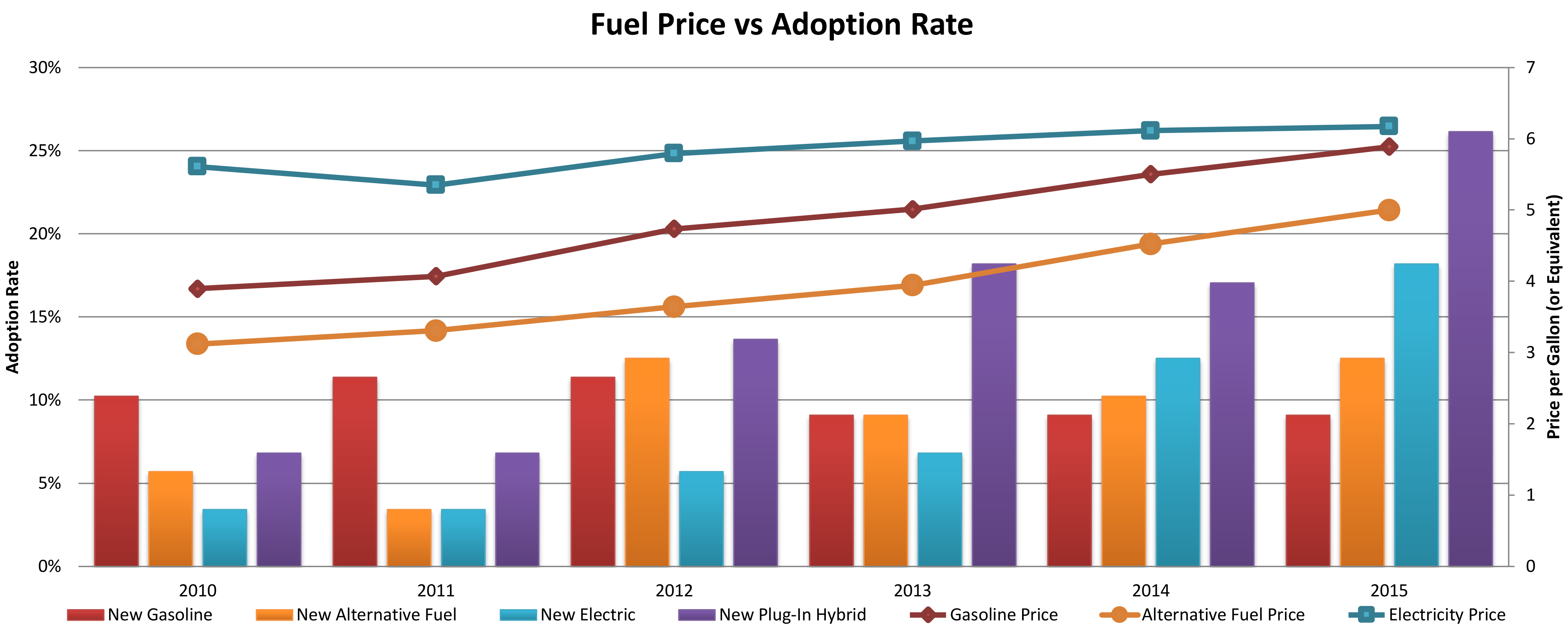
Which option would you prefer for your vehicle ownership in **2013**?

- **I Will KEEP My Current Vehicle**
- **I Will BUY a Gasoline Vehicle (or normal hybrid) that runs on Gasoline**
- **I Will BUY an Alternative Fuel Vehicle that runs on Alternative Fuel**
- **I Will BUY a Diesel Vehicle that runs on Diesel Fuel**
- **I Will BUY an Electric Vehicle that runs on Electric Fuel**
- **I Will BUY a Plug-In Hybrid Electric Vehicle that runs on Gasoline and Electric Fuel**
- **I Will SELL My Current Vehicle and NOT REPLACE It**

What’s next?

- Thanks to:
- Yangwen Liu
- Yan Liu
- Michael Maness
- Jean Michel tremblay

Results – Fuel Technology



Static Model- results

Alternative	gas	hybrid	electric	current	MNL Estim	MNL t-Stat
ASC2		X			-0.4044	1.6
ASC3			X		-0.50	0.9
ASC4				X	1.52	3.2
mpg_known	X	X			0.052	4.0
mpg_unknown	X	X			0.016	2.1
veh_age				X	-0.097	4.3
price_st	X	X			-0.26	1.8
price_dy			X		-0.37	2.4
range			X		0.44	2.1
N observed					530	
LL(0)					-734.74	
LL(final)					-614.66	
likelihood ratio index					0.22	

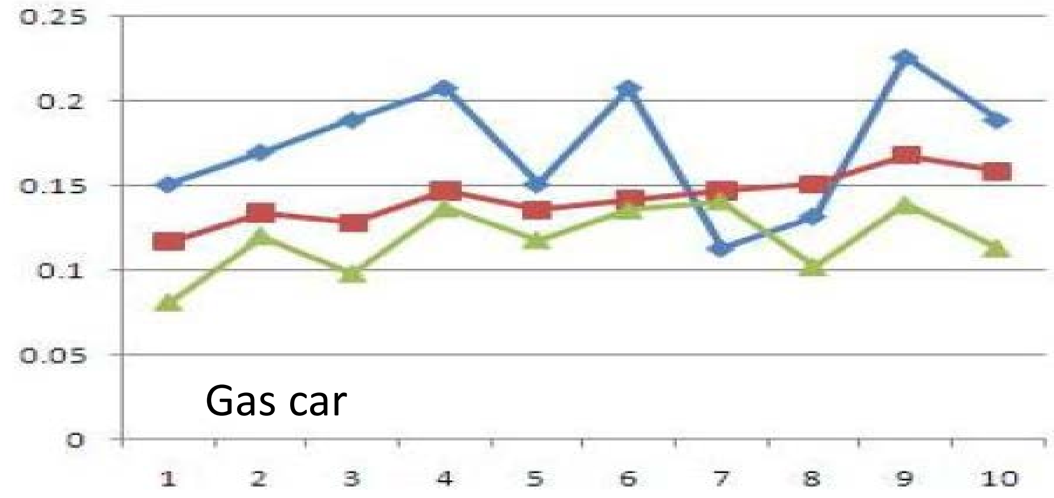
Dynamic model -results

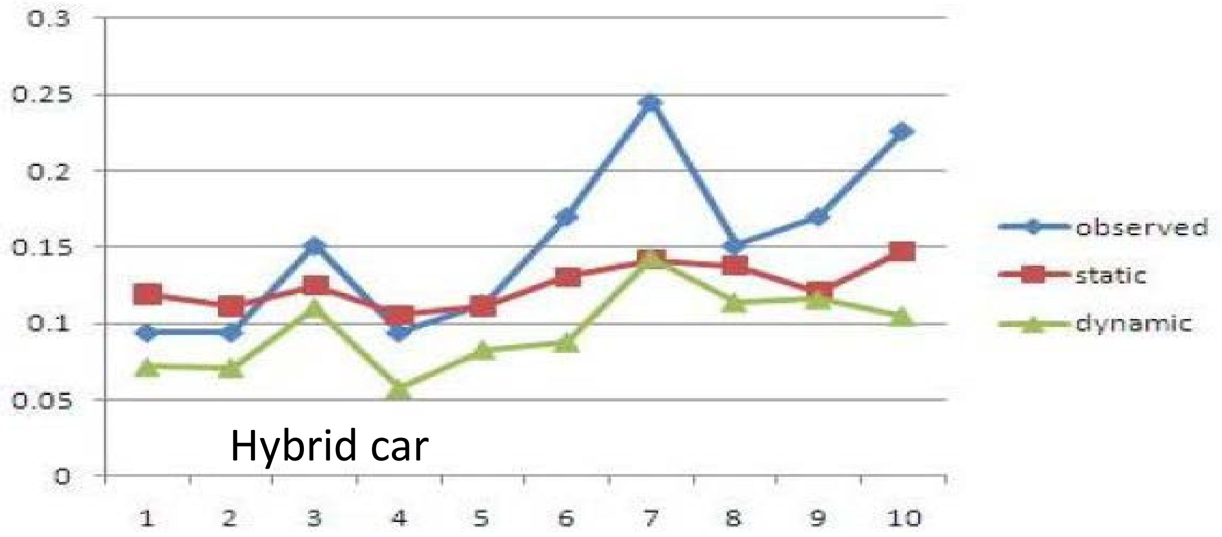
Choose electric car price as the dynamic variable

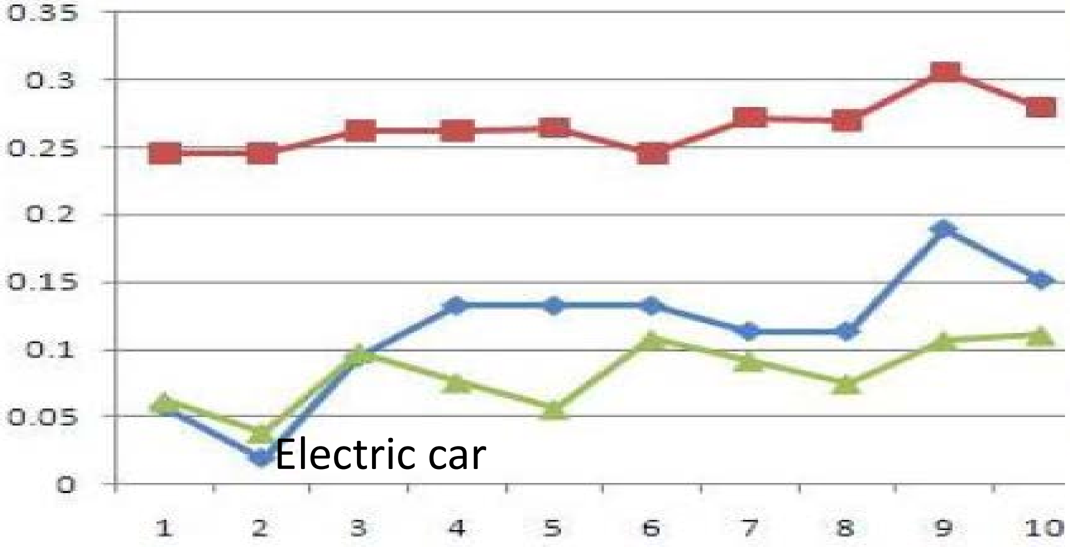
$$y_{j,t+1} = -0.103 \times y_{jt} + 2.617 + N(0,1.78)$$

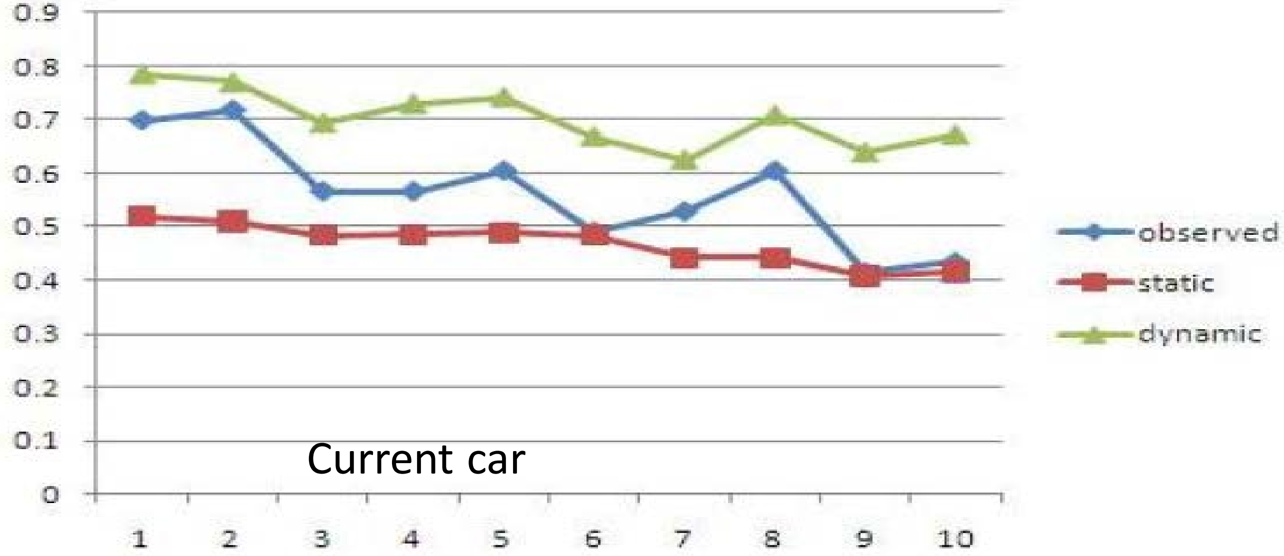
Alternative	gas	hybrid	electric	current	Dynamic	
					Estim	t-Stat
ASC2		X			-1.09	4.05
ASC3			X		1.18	1.94
ASC4				X	-1.10	6.96
mpg_known	X	X			0.078	6.20
mpg_unknown	X	X			0.042	3.66
veh_age				X	-0.133	4.26
price_st	X	X			-0.062	0.46
price_dy			X		-1.01	5.37
range			X		0.723	4.32
N observed					636	
LL(0)					-1683.09	
LL(final)					981.43	
likelihood ratio index					0.42	

Market shares - comparison









Conclusions

- New gasoline vehicles, hybrid and electric vehicles occupy smaller market shares (around 10% each) at the end of the five year period;
- All new typologies become more popular after the fifth time period;
- Static models are incapable of recovering peaks in the demand function;
- MNL model underestimates the market share of the "not buy", and dramatically overestimate the share occupied by electric vehicles in the next five years;
- Dynamic model overestimates the market share of the "not buy", but is capable to reproduce the descending trend for this alternative.