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Opportunities and Challenges of Incorporating Consumer Choices and Consumer Behavior in Energy–Economy–Engineering–Environment (4E) models to Analyze Policies

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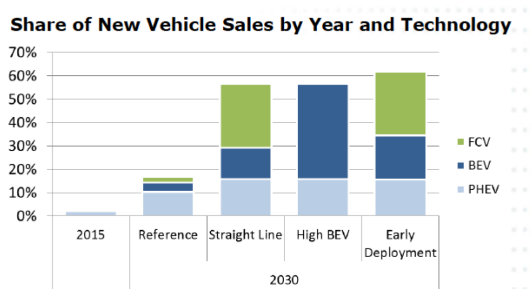
Motivation

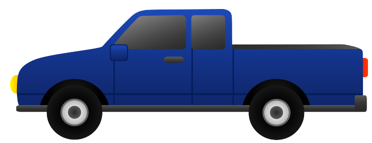
- High-level motivation:
  - **Developing improved models for analyzing policies related to *climate change*.**
  - **These involve evaluation of alternative future energy pathways that rely on introduction of new technologies.**
- The specific problem with we seek to address:
  - **Models frequently include a high level of detail on technology performance and costs, but,**
  - **They fall short in producing realistic consumer response to alternative future market scenarios.**

The Big Gap between Scenario Analysis and Consumer Preferences

Scenario Model: If we do everything technically feasible…

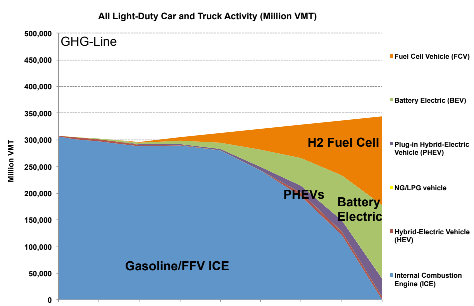
- **6-7 million ZEVs and PHEVs on the road by 2030**

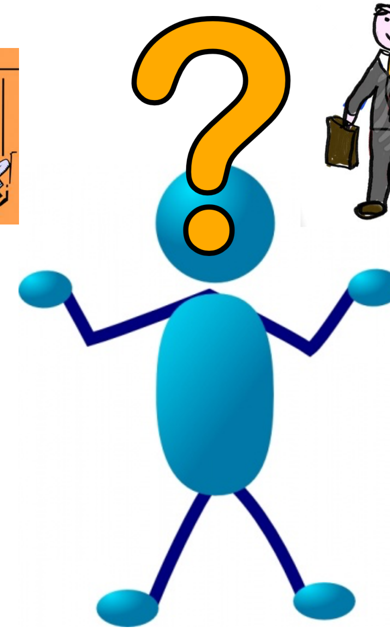




Optimization Model: If we need to meet the policy objective, the least cost pathway is….

2.4 million vehicles (~1.1M BEV/PHEV, 1.3MFCV) in 2030





CGEs: If we shock the system with climate policies, what would be the direct and indirect economic impacts…

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Today's Presentation

Part I. Policy and Incentive Strategies to Incentivize PEV adoptions in California

Yeh, Sonia, David Bunch, Kalai Ramea, Christopher Yang, Jeff Kessler, and Gustavo Collantes. Policy and Incentive Strategies to Incentivize Plug-in Electric Vehicle (PEV) adoptions in California. Draft Manuscript.

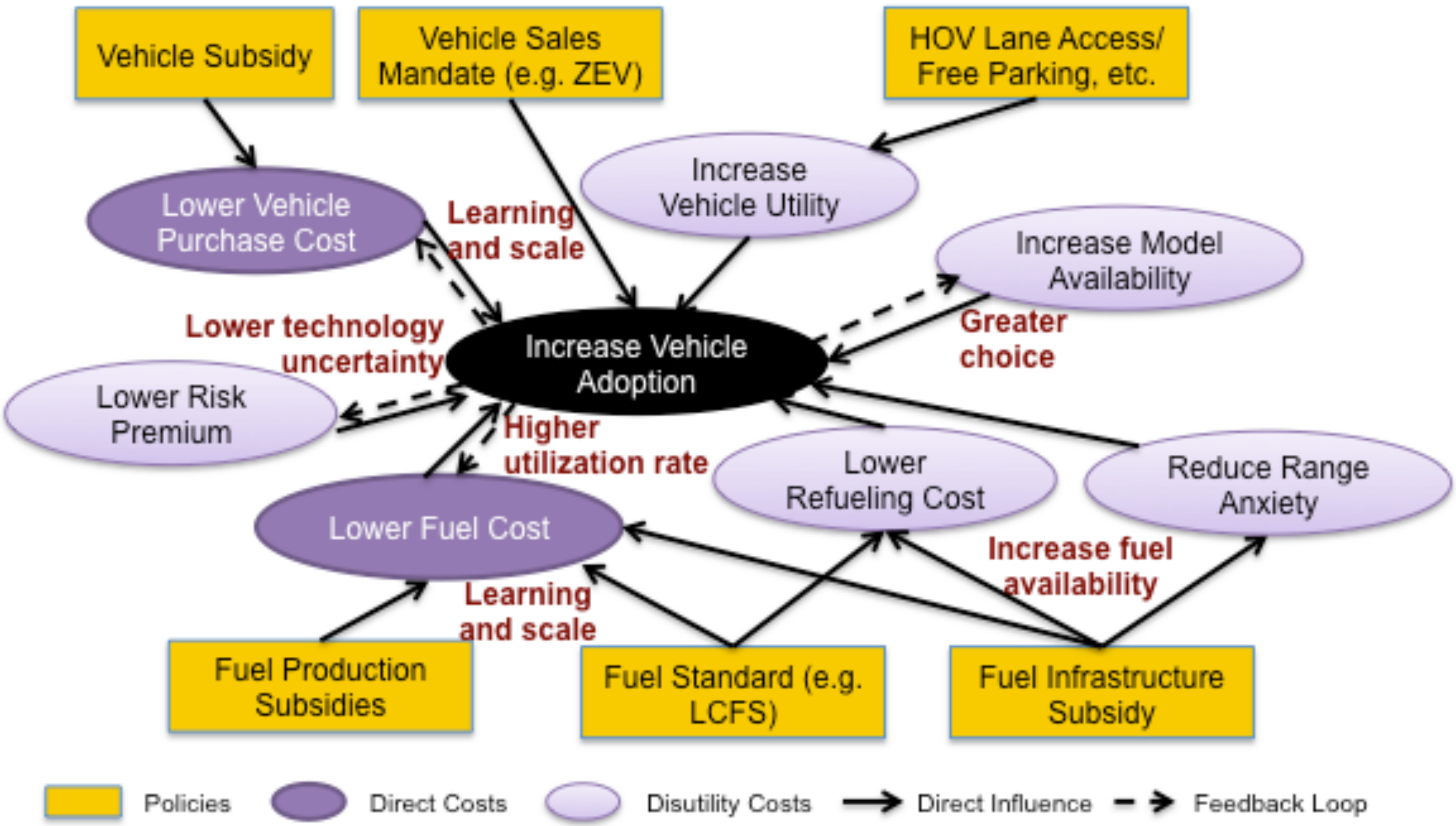
Part II. Incorporating Behavioral Effects into Bottom-Up Energy Models

Bunch, David S, Kalai Ramea, Sonia Yeh, and Christopher Yang. Incorporating Behavioral Effects from Vehicle Choice Models into Bottom-Up Energy Sector Models. Draft Manuscript.

Motivation:
Policy and Incentive Strategies

- Provide insights and conclusions about the relative efficacy of various **non-regulatory** policies and programs for supporting a successful transition to alternative vehicles and fuels, consistent with California's long-term GHG goals.
  – How do these non-regulatory policies and programs can be used to help lowering barriers to develop markets for new alternative fuel vehicles and clean fuels
  – Support and complement regulatory programs that establish policy requirements to be met by various stakeholders.
  – Annual program budget of approximately $100 million
  – A portion of $1Billion cap-and-trade revenues

Relations between Policies and Vehicle Adoptions



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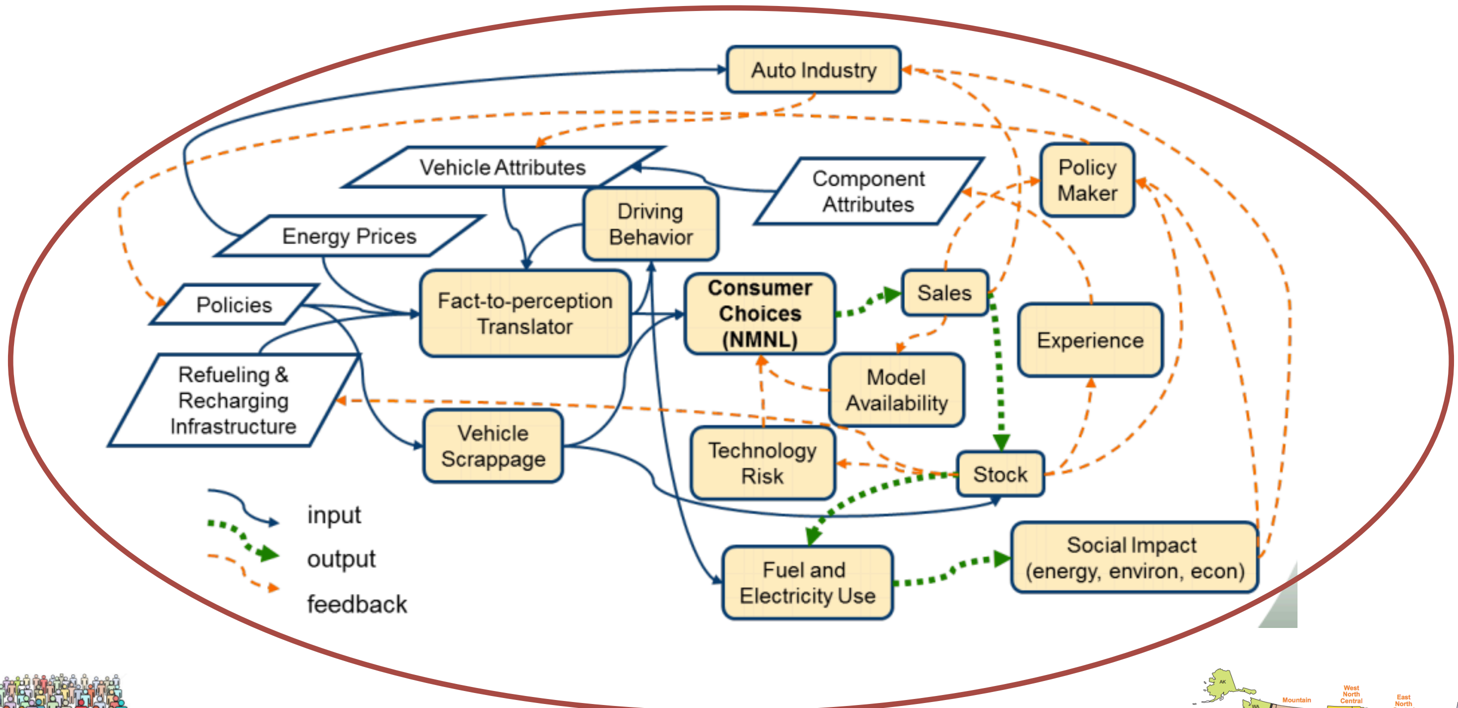
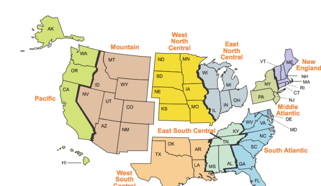
Yeh, Bunch et al. Policy and Incentive Strategies to Incentivize PEV adoptions in California

MA^{3}T Consumer Choice Model

MA^{3}T (Market Allocation of Advanced Automotive Technologies), nested multinomial logit model developed by Oak Ridge National Laboratory



1458 consumer groups (Regions, driving behavior, risk attitude, charging infrastructure)



Nationwide Model (9 regions in the US)

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OAK RIDGE National Laboratory

Disutility Cost

- MA^3T model generates a cost term called "generalized cost" that has the direct and indirect cost components
  - Direct costs: Vehicle prices, fuel costs
  - Indirect costs or **disutility cost** components:
    - Refueling station availability
    - Range Anxiety cost
    - Model availability
    - New technology risk premium
    - Towing capability

Infrastructure

Vehicle attributes

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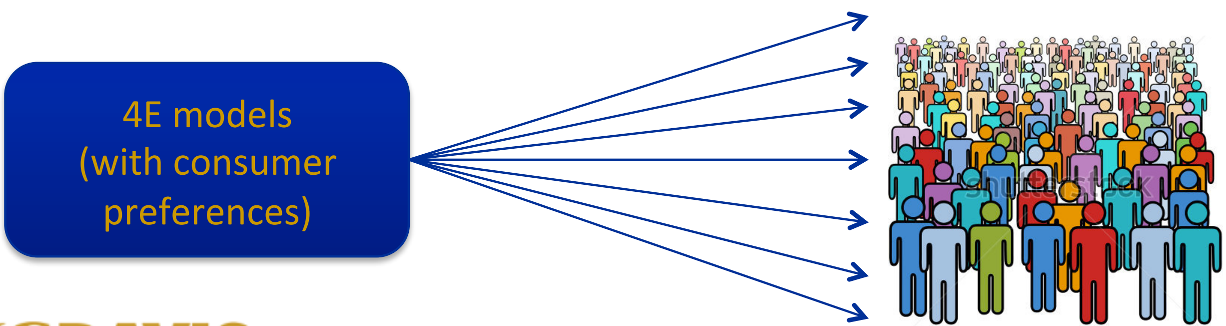
Motivation for Consumer Choice

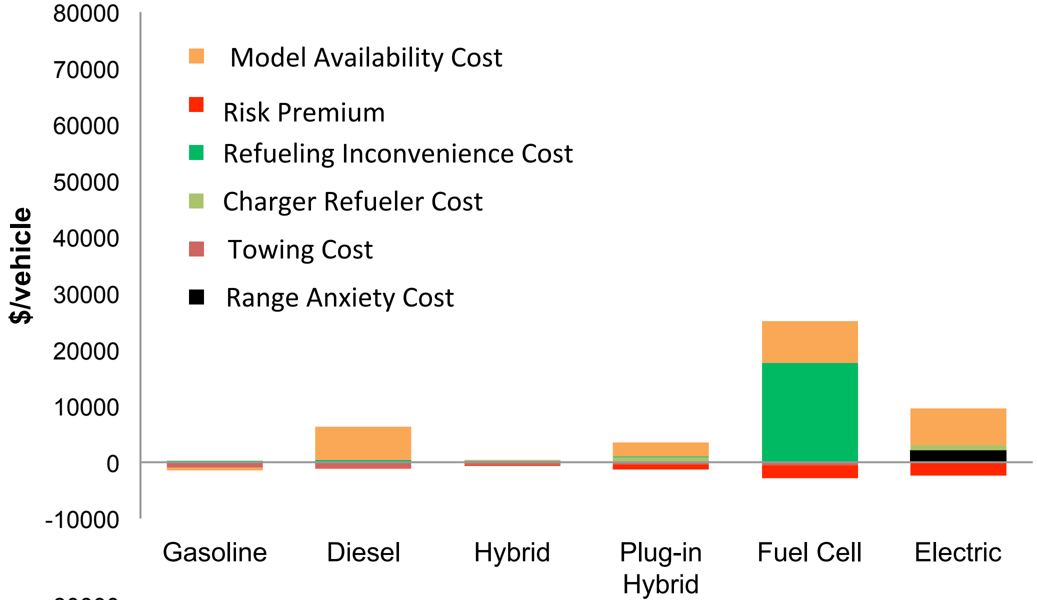
- System-engineering models typically assume society is homogenous, i.e. there is only one decision-maker at the societal level
- Consumer behavior cannot be ignored in system-wide modeling!
- One objective of this project is to develop a bridging approach to bring in consumer behavioral parameters, to the linear programming framework of TIMES

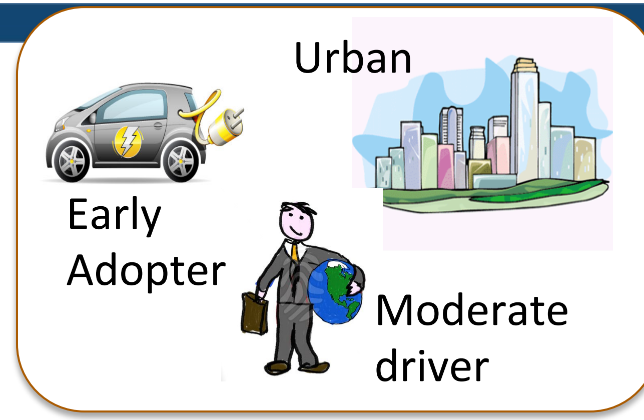
4E models typically are linear optimization models

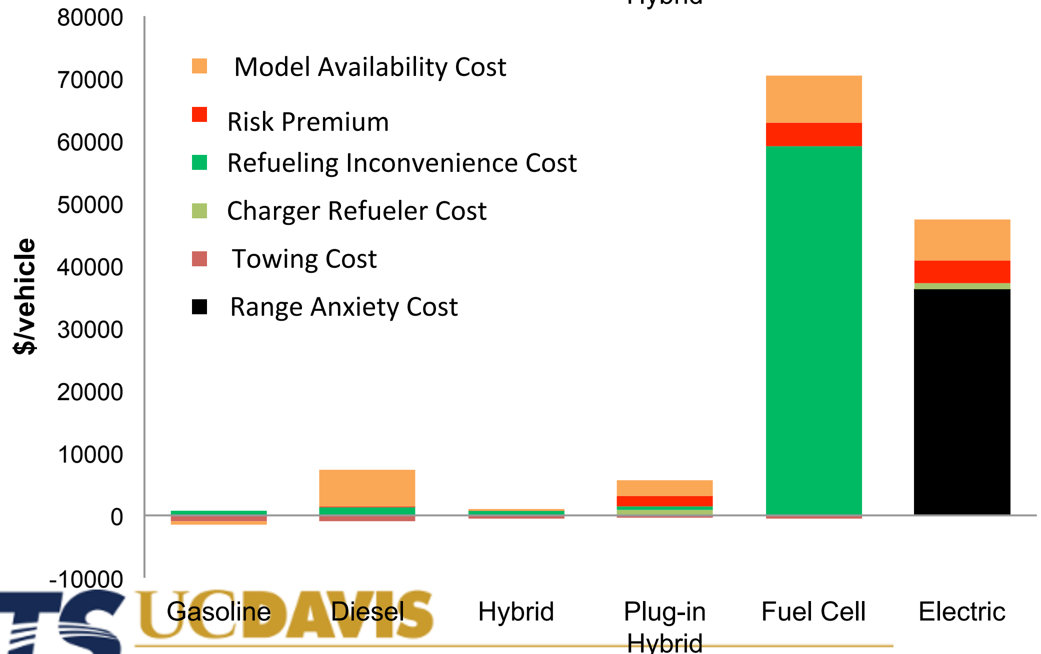
"Winner takes all" phenomenon (least cost optimization)

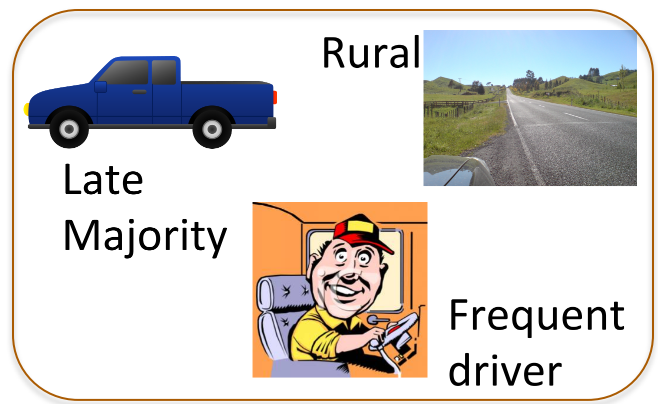


Components of Disutility Cost in the year 2020

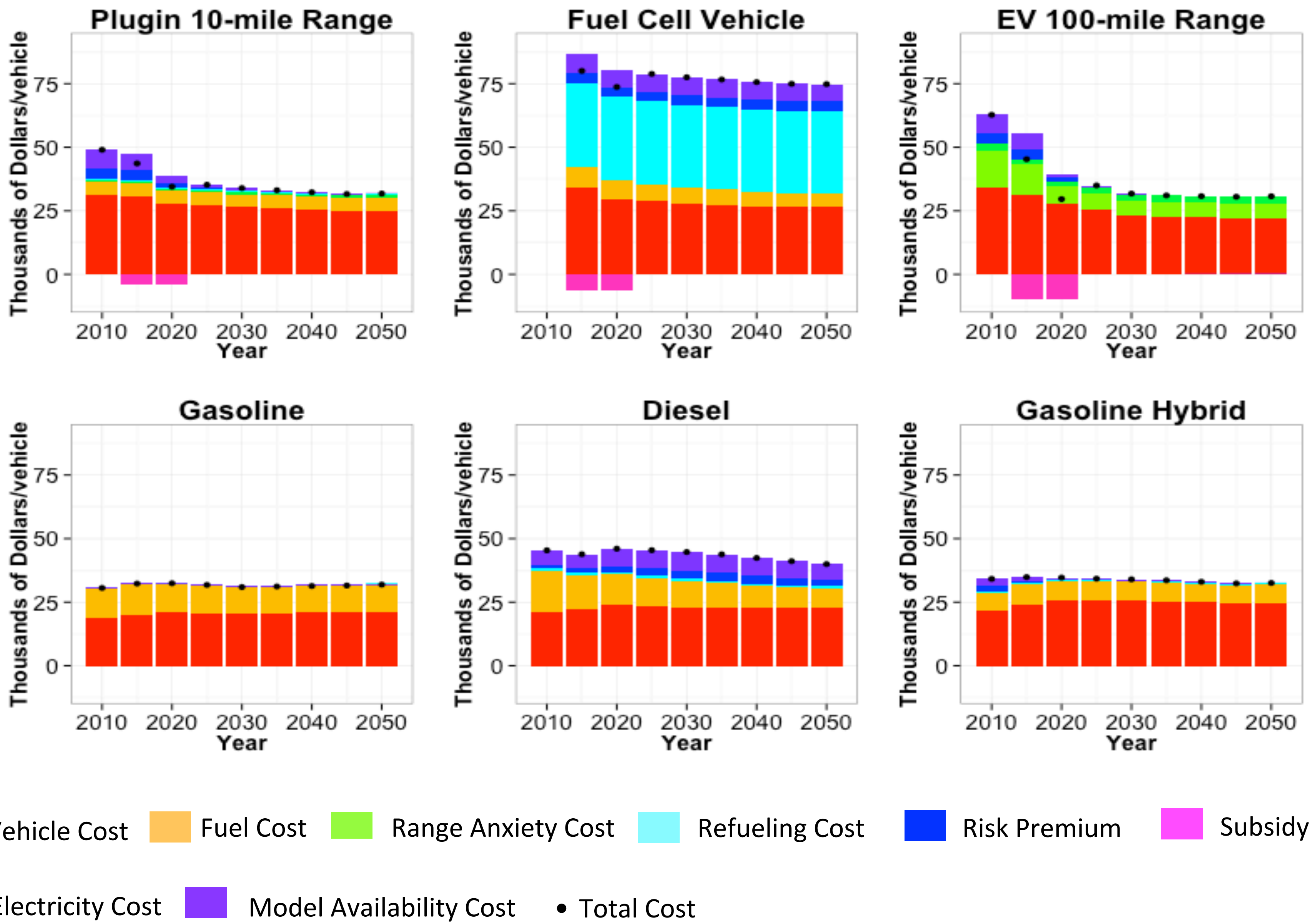








Cost Components: Late Majority, High Annual VMT



Summary of Scenario Results

	ZEVs on the Road in CA (Millions)		
Scenario Name	2020	2025	2050
Reference	0.437	0.813	6.882
State vehicle subsidies extended to 2025	0.548	1.273	6.967
Public recharging expansion	0.439	0.828	7.063
Workplace recharging expansion	0.439	0.820	7.302
Hydrogen station expansion	0.437	0.822	7.036
Public + Workplace expansion	0.440	0.835	7.485
Public + Workplace + Hydrogen ('All three')	0.440	0.844	7.630
All three + Subsidies to 2025	0.552	1.337	7.722
Scenario 2 + federal tax credits to 2019	1.104	2.320	7.325

Preliminary Estimates of Return on Investments

- Scenario 2 (subsidies): $5,300 per additional vehicle
  - the size of this figure (which is larger than the per-vehicle subsidy amounts) is due to the fact that some ZEV sales would have occurred anyway, without the subsidies.
- Scenario 3 (charging stations): $950 per additional vehicle
  - an estimated increase of 15,000 ZEVs in 2025, versus an estimated cost of $13.5M (from adding 500 recharging locations),
- Scenario 5 (H2 station): $6,500 per additional vehicle
  - hydrogen station option involves an increase of 40 hydrogen stations between 2020 and 2025 at an estimated cost of $60M.
  - We assume the average cost of hydrogen refueling station is $1.5 million per station.

Key Observations

- Reference scenario (includes currently planned infrastructure, federal tax credits and state-sponsored vehicle purchase subsidies through 2017) suggest that meeting the 1.5 million ZEV on the road target by 2025 would likely *not* occur, and that extending state vehicle subsidies to 2025, while very helpful, could also fall short
- Potentially critical role played by factors related to technology legitimation, and the dominating influence of the larger vehicle market.
- **Major importance of recent and future multistate efforts intended to address all aspects of market formation for clean fuel vehicles, and legitimation of new vehicle technologies**

Part II. Incorporating Behavioral Effects into Bottom-Up Energy Models

Desirable Qualities in an Integrated Model

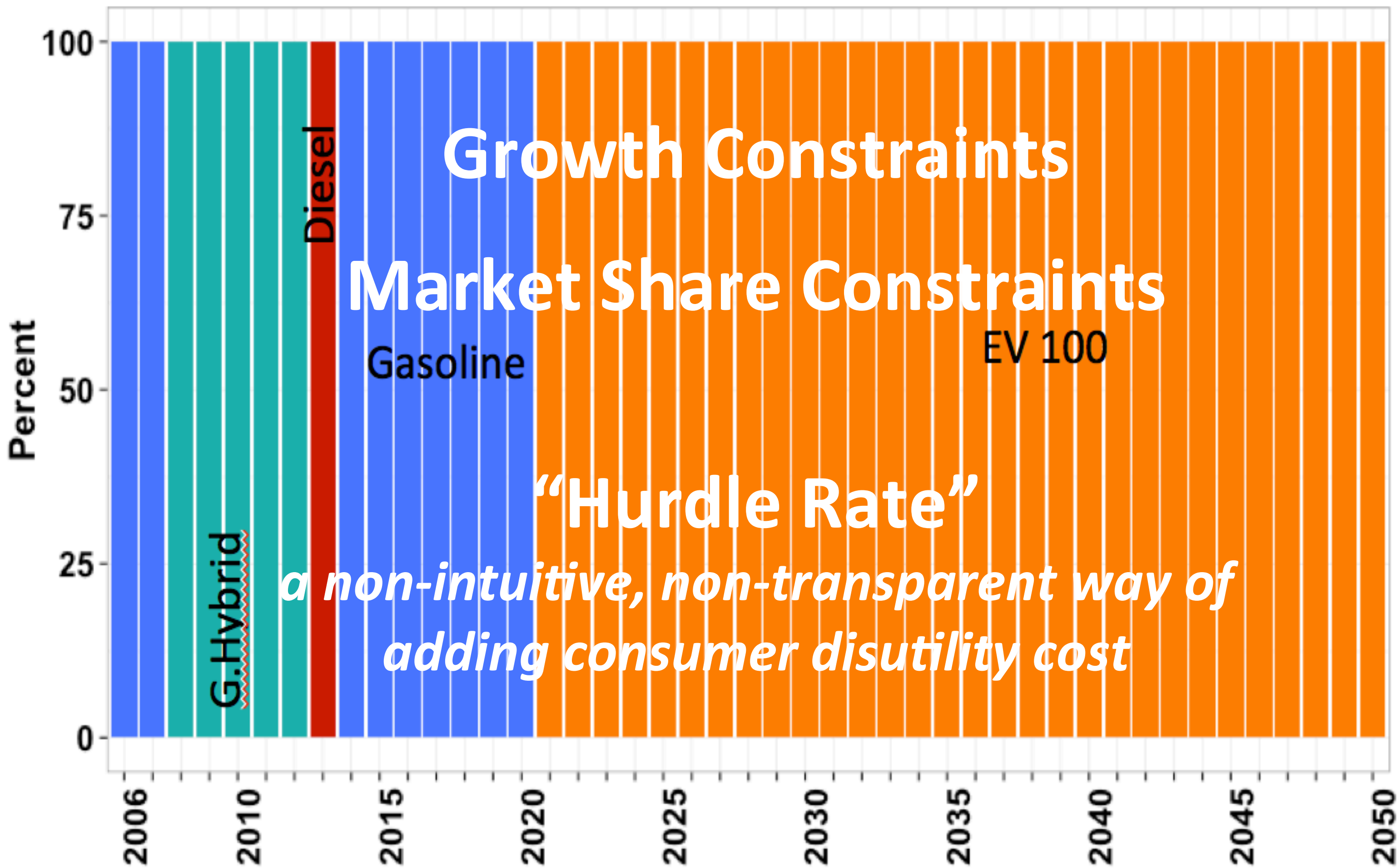
Objective: How can we combine the strengths of choice and energy modeling approaches ?

- Be able to capture qualitative parameters as part of decision-making process
- Be able to include consumer heterogeneity on the demand-side
- Be compatible with the linear-optimization framework of TIMES

New Car Technologies

- **Conventional**
  - **Internal Combustion**
    - Gasoline
    - Diesel
    - Natural Gas
  - **Hybrid**
    - Gasoline
    - Diesel
    - Natural Gas
  - **Gasoline Plugins**
    - 10-mile
    - 20-mile
    - 40-mile
- **Hydrogen**
  - Hydrogen ICE
  - Fuel Cell Vehicle
  - **Fuel Cell Plugins**
    - 10-mile
    - 20-mile
    - 40-mile
- **EVs**
  - 100-mile
  - 150-mile
  - 250-mile

LP Model => 'Knife Edge Behavior'



The Nature of the Problem

Uses a Linear Programming formulation.

The **LP objective function** looks like:

$$NPV = \sum_{y \in YEARS} (1 + d_y)^{REFYR-y} (ANNCOST(y) + FIXCOST(y) + VARCOST(y) + ELASCOST(y) + \cdots)$$

where,

NPV = net present value of the total system costs;
d_y = general discount rate;
REFYR = reference year for discounting;
YEARS = set of years have costs, including all years in horizon;
ANNCOST = annual costs of investment = CRF*INVCOST
FIXCOST = fixed annual costs;
VARCOST = variable annual costs;
ELASCOST = cost of demand reduction

= 0 when the model uses cost minimization (without elastic demand)

Steps to Combine Choice Model with Linear Optimization

- Using optimization to mimic the “behaviors” of choice model by:
  - Creating consumer groups (heterogeneity in demand)
  - Creating clones (heterogeneity in preferences)
  - Adding disutility terms (consumers maximizing utilities rather than simply minimizing NPV of technology and fuel costs)
  - Adding Random Disturbance Terms (nested multinomial logit)

Background – cont-

- All models start with assumptions about how **Households** and **Firms** make **decisions.**
- **Firms** are assumed to “maximize profits”.
- **Households** are assumed to “maximize utility, subject to a budget constraint”:

$$\max_{\mathbf{q}} U(\mathbf{q})$$

$$s.t. \sum_{j=1}^{C} p_j q_j = y$$

$$\mathbf{q} \geq 0$$

Let p_j = annual rental price
$\Rightarrow$ q_j = number of vehicles of type j rented.
$\Rightarrow$ y = budget

But, we need (more) Behavioral Content!

- Need to *modify* the (general) direct utility function U:
- Add in these factors:
  - Vectors of vehicle attributes x_j, $j=1,\ldots, J$ [$\mathbf{x} = \{x_j\}$]
  - Vector of household characteristics $\mathbf{d}$.
  - Also, if the goal is econometric/statistical models of behavior for empirical analysis:
    - Add an unobservable disturbance term (ε_j) for each vehicle j.
    - Perhaps unobservable household characteristics (ξ).
    - And: A vector of preference parameters (β)
  - So that:

$$U(\mathbf{q},z) \rightarrow U(\mathbf{q},z;\mathbf{x},\mathbf{d},\beta,\varepsilon,\xi)$$

After some heavy mathematics…

- The solution to the previous problem can be presented in terms of conditional, indirect utility, defined by

$$V(y-p_j;\mathbf{x}_j,\mathbf{d},\beta,\varepsilon_j)=U(0,\ldots,1_j,\ldots,0,y-p_j;\mathbf{x},\mathbf{d},\beta,\varepsilon_j),\ j=1,\ldots,J$$

- At the individual level for a particular household, they choose the vehicle with the maximum value of V_j. When doing analysis, we consider the choice probability for vehicle *c* defined by:

$$\pi_c=\mathrm{Prob}\left\{V(y-p_c;\mathbf{x}_c,\mathbf{d},\beta,\varepsilon_c)\geq V(y-p_j;\mathbf{x}_j,\mathbf{d},\beta,\varepsilon_j),j=1,\ldots,J\right\}$$

Traditional “RUM” Motivation for DCMs

- Most papers on discrete choice models use the previous slide as a starting point. They call this “Random Utility Maximization” (RUM), and frame it based on (conditional) indirect utility:

$$V_j = \bar{V}_j + \varepsilon_j,\ j = 1,\ldots,J$$

- Without reference to the original standard model.

- The most frequently used model is multinomial logit (MNL):

$$\pi_c = \frac{e^{\mu \bar{V}_c}}{\sum_{j=1}^{J} e^{\mu \bar{V}_j}},\ c = 1,\ldots,J$$

COCHIN-TIMES model

- **<u>CO</u>**nsumer **<u>CH</u>**oice **<u>IN</u>**tegration in TIMES
- Illustrative tool that represents only light-duty car technologies for the California region
- Does not predict the future, but a learning tool to simulate how different parameters might affect vehicle purchase choices
- 20 light-duty car technologies, 27 consumer groups
- Vehicle prices, fuel efficiency and fuel prices are obtained from AEO 2014 data

Bunch, Ramea et al. (2015) Incorporating Behavioral Effects into Bottom-Up Energy Models

Injecting MA³T Generalized Costs into TIMES

- 1. Vehicle and fuel prices + efficiencies
- 2. + 3 VMT groups (low, average high)
- 3. + ‘Refueling Inconvenience Cost’
- 4. + Range-Limitation/Recharging Infrastructure Costs
- 5. + Model Availability Costs
- Are we done? No!
- There is also the matter of random variation in consumer preferences!
- Up until now, what we have added (for multiple consumer groups) is:

$$\underbrace{r_j}_{\text{fixed cost}} + \underbrace{p_j q^*}_{\text{operating cost}} - \underbrace{\left(\alpha_j + \sum_k \beta_k b_{jk}\right) q^*}_{\text{generalized cost}}$$

Injecting MA³T Generalized Costs into TIMES

- We can generate 'clones' for each consumer group by generating an appropriate set of random disturbances (based on the MA³T model):

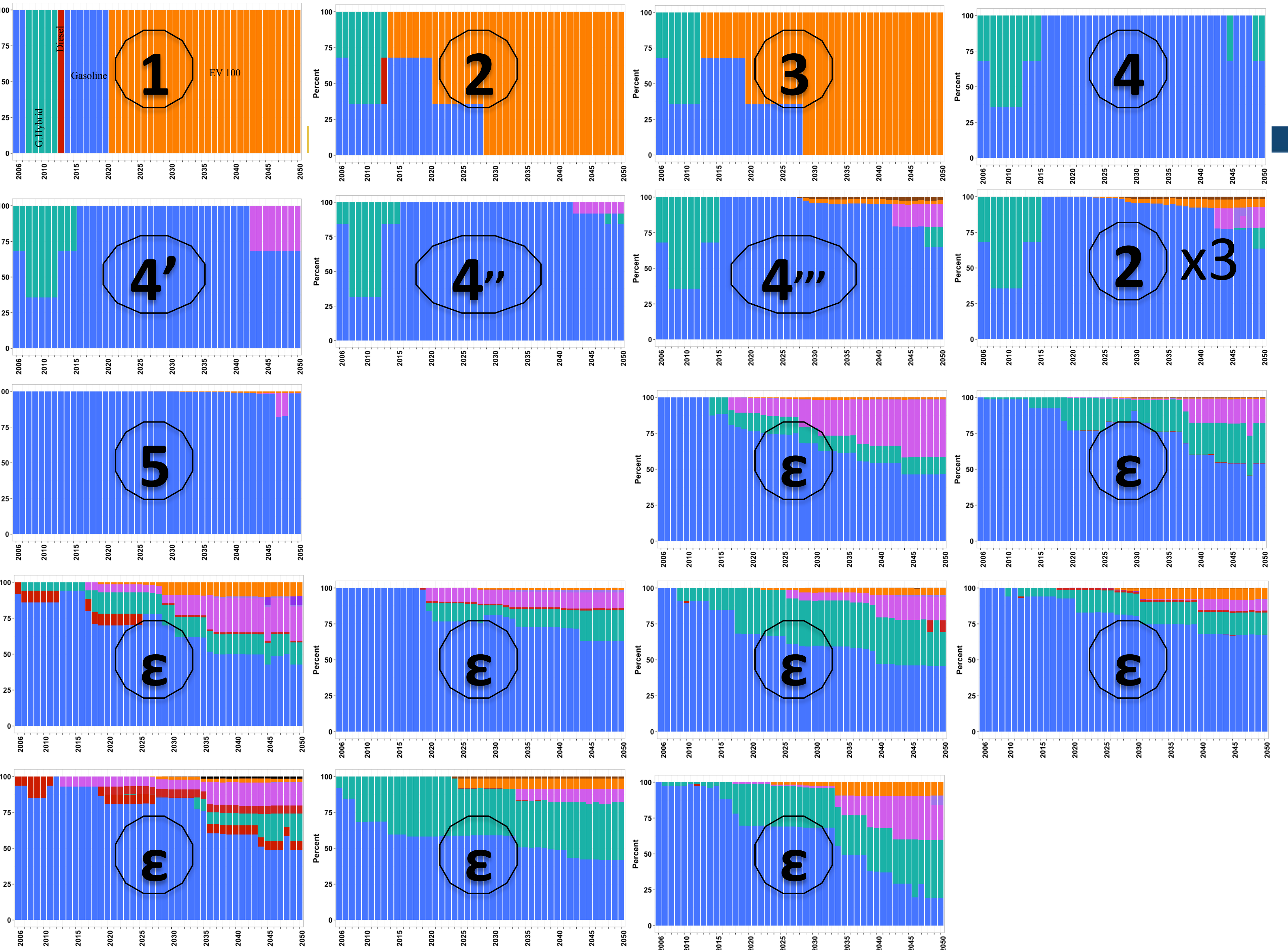
$$r_j + p_j q^* - \left(\alpha_j + \sum_k \beta_k b_{jk} \right) q^*$$

$$\downarrow$$

$$r_j + p_j q^* - \left(\alpha_j + \sum_k \beta_k b_{jk} \right) q^* - \varepsilon_{j1}^*$$

$$\vdots$$

$$r_j + p_j q^* - \left(\alpha_j + \sum_k \beta_k b_{jk} \right) q^* - \varepsilon_{jN}^*$$


1
G.Hybrid
Diesel
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Percent
0
25
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2006
2010
2015
2020
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2040
2045
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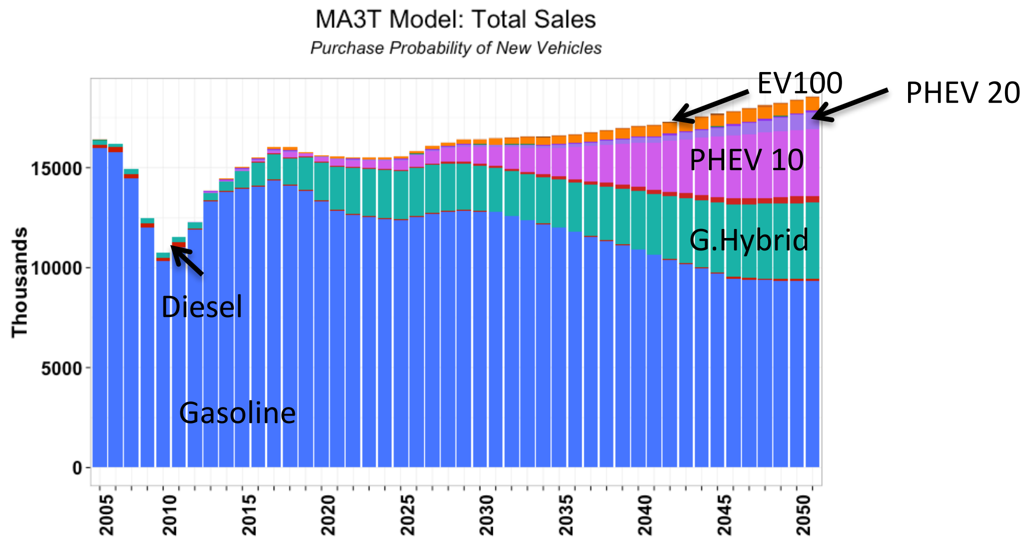
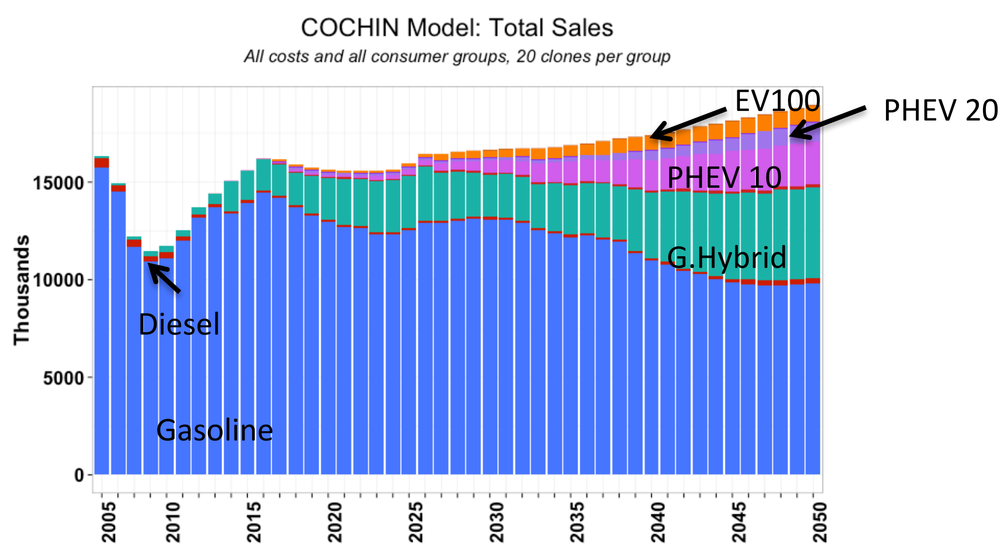
Total Sales Numbers

Total LDV sales numbers are taken from AEO 2014 Sales Numbers





Summary and Work in Progress

- COCHIN LDV-only model mimics consumer choice behavior similar to MA^3T model for various scenarios
  - Demand heterogeneity
  - Disutility or generalized costs
  - Random error distribution added as 'costs' to introduce nested-logit structure
- Currently the COCHIN methodology is being integrated in the full CA-TIMES model
  - Endogenous station availability determination
  - Better representation of spatiality
  - Policy analysis such as carbon cap, infrastructure investment, vehicle subsidies

Challenges of Modeling Consumer Choices

- Fundamental theories and mathematical formulations
  - For bottom-up models, there is a need to shift from *cost minimization* to *utility maximization subject to budget constraint* that is typically in the realm of CGE models
- Basic Understanding of consumer
  - "Need more research in social and political science as well as psychological and consumer behavior research"
  - Consumer preferences are not static given shifts in tech attributes
- Data
  - "Household types, income, split of income across sources, and consumption choices"
  - Greater spatial and temporal resolution

Why Representing Consumer Heterogeneity?

- Useful to examine benefits of policy interventions that target particular subgroup(s).
- Useful to examine disruptive technologies/policies

What Affect Consumers' Choices?
— and how policies (models) can be introduced to improve the status quo

- Information
  - More information reduce search costs and increases the likelihood of "rational outcomes."
- Social interactions and social norms
  - Influencing the disabilities of social norms
- Risk averse attitude toward unknowns

These three factors interact with each other

Sources of Prediction Errors

1. Non-optimizing consumer behavior (omitted variable biases)
2. Aggregate MNL model applied to heterogeneous consumers
3. Errors in MNL model structure
4. Errors in MNL parameters (disutility terms and how they change over time)
5. Omitted variables (including manufacturer pricing decisions)
6. Changes in consumers' behaviors and preferences over time
7. Inaccurate representation of learning (learning rate, spillover between California markets and the national markets)
8. Regional differences in consumer choices and consumer behaviors

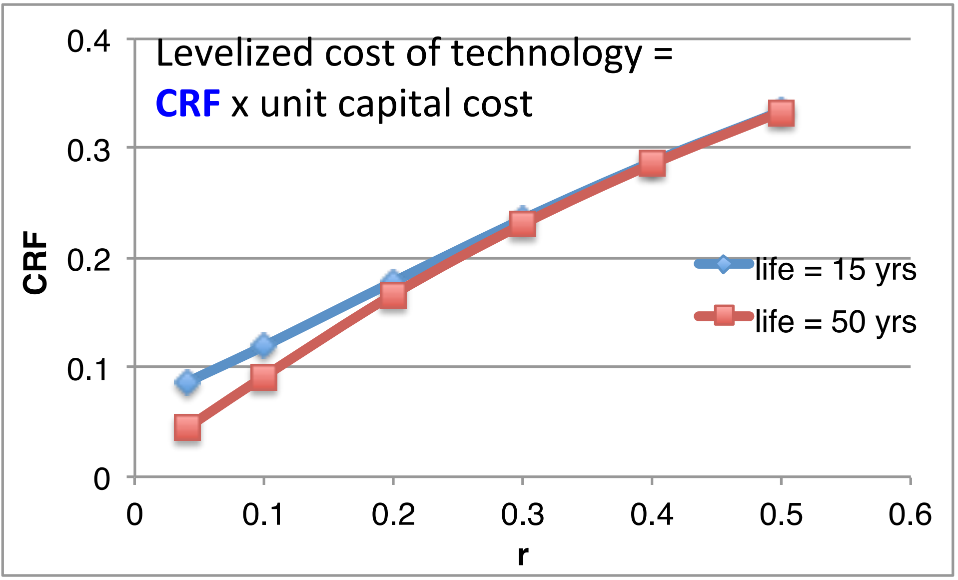
Adapted from EPA, U. S. (2012). Consumer Vehicle Choice Model Documentation, Prepared for U.S. Environmental Protection Agency by Oak Ridge National Laboratory EPA Contract No. DE-AC05-00OR22725.

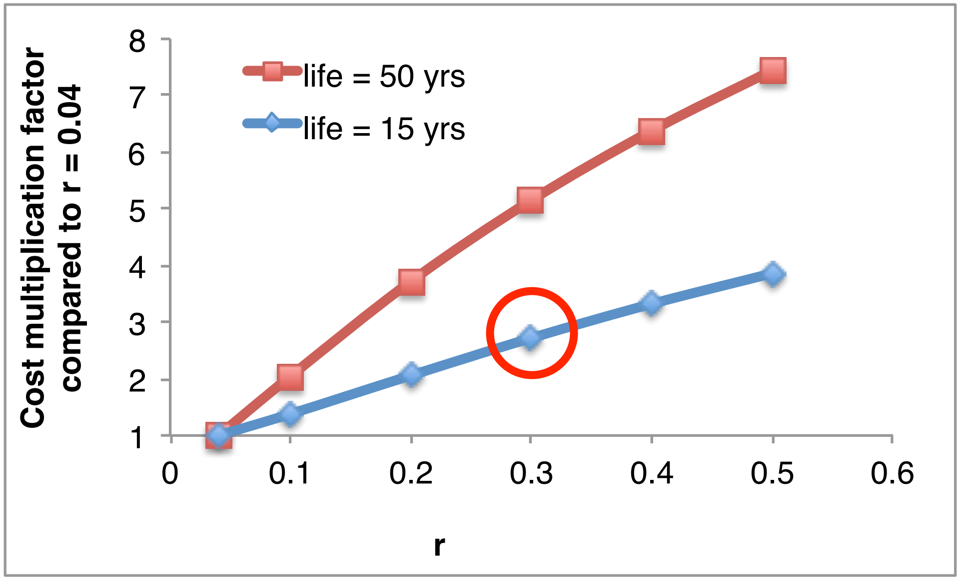
Additional Resources

- Yeh, Sonia, David Bunch, Kalai Ramea, Christopher Yang, Jeff Kessler, and Gustavo Collantes. 2015. "Policy and Incentive Strategies to Incentivize Plug-in Electric Vehicle (PEV) adoptions in California." Draft manuscript.
- Bunch, David S, Kalai Ramea, Sonia Yeh, and Christopher Yang. 2015. "Incorporating Behavioral Effects from Vehicle Choice Models into Bottom-Up Energy Sector Models." Draft manuscript.
- David S. Bunch. Incorporating Behavioral Effects from Vehicle Choice Models into Bottom-Up Energy Sector Models. ITS seminar. May 8, 2015 http://www.its.ucdavis.edu/seminar/may-8-2015/

BACKUP SLIDES

Use of high "Hurdle Rate" is a non-intuitive, non-transparent way of adding consumer disutility costs





- Typical assumptions for vehicles are
  - hurdle rate (r) = 0.3 ➔ 3 yr payback period
  - average vehicle lifetime = 15 yrs
- Cost multiplication factor = 2.7 to the levelized cost of technology with a high discount rate compared with using a social discount rate

… compared to a more transparent "generalized cost"