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# Modeling Technological and Behavioral Response to Transport Policies

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Workshop on Transport Modeling in IAMs

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# Key points

I explain how we pursue greater technological and behavioral detail in a nationally-focused hybrid simulation model. (The work of many researchers over at least a decade.)

I explain the empirical research to estimate key parameters and their potential dynamism over time.

I also explain how this work can inform less detailed, global models.

Why? Policies are often technology and fuel specific (regs, subsidies), and they may try to change the decision context (urban form, transit and other non-vehicle options, road pricing).

Why not? Potentially overwhelming in terms of data and research needs and model complexity.

# Hybrid models (e.g., NEMS, CIMS)

Combine the useful attributes of bottom-up (technological explicitness) and top-down (behavioral realism, equilibrium feedbacks)
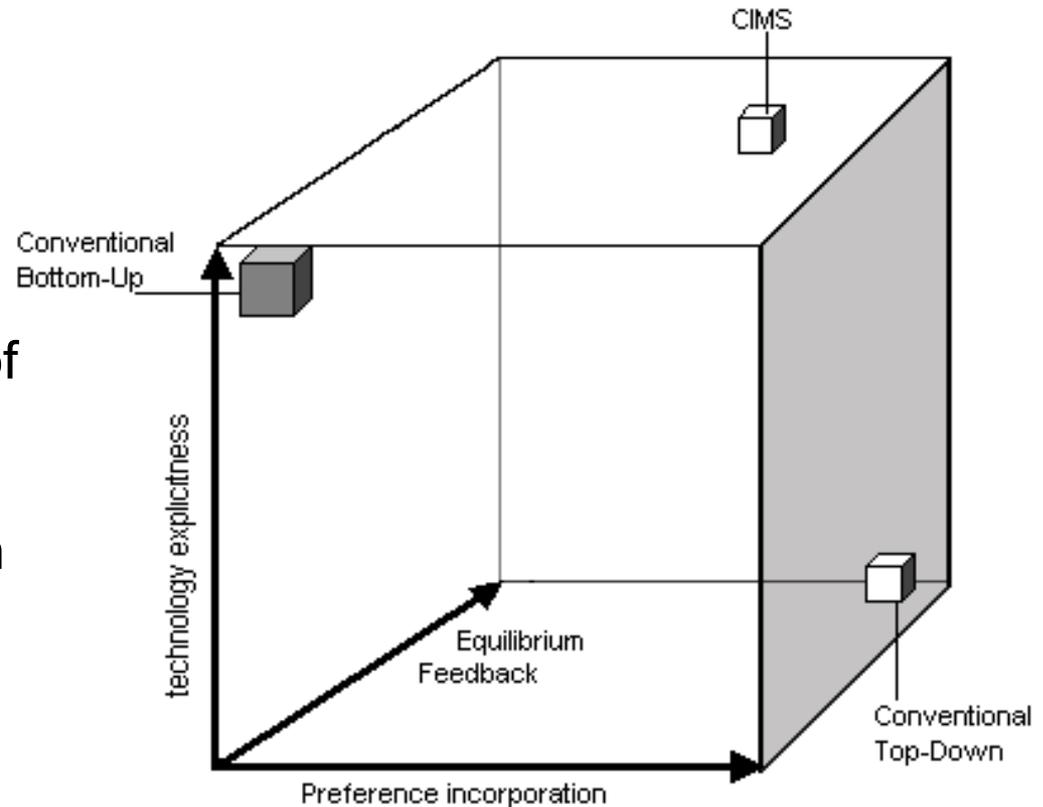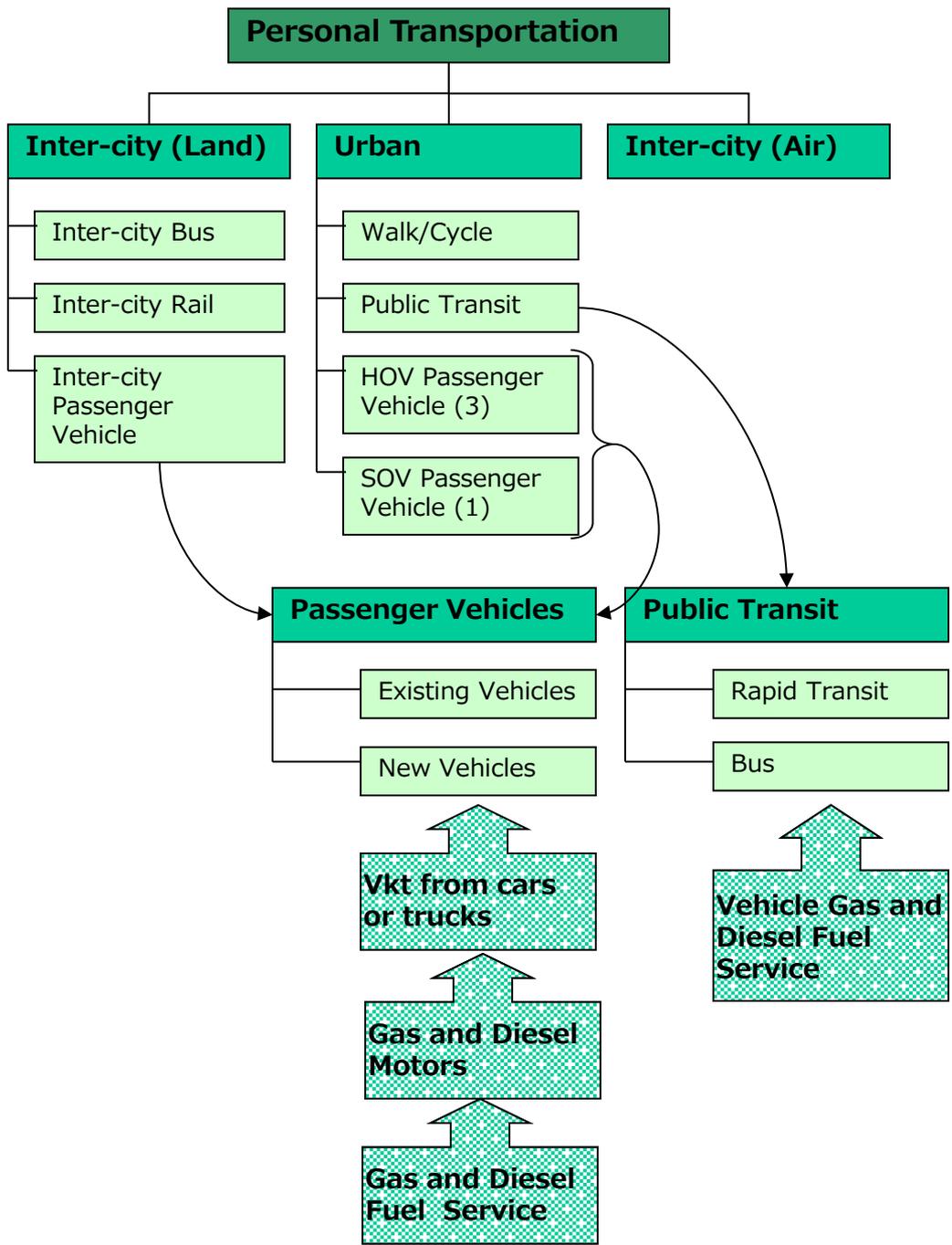


Jaccard, 2009, "Combining top-down and bottom-up in energy-economy models" in Evans and Hunt (ed.), International Handbook on the Economics of Energy.

# CIMS: technology vintage model

1. Retire oldest stock (age-dependant)

2. Forecast demand – initial exogenous forecast adjusted by endogenous energy price and macroeconomic feedbacks (including service demand for personal mobility and freight)

3. Retrofit existing stock if economic (technology choice algorithm)

4. Calculate new stock purchase (demand minus existing stock)

5. Acquire new stock as needed (technology choice algorithm)

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```
Personal Transportation
├── Inter-city (Land)
│   ├── Inter-city Bus
│   ├── Inter-city Rail
│   └── Inter-city Passenger Vehicle
├── Urban
│   ├── Walk/Cycle
│   ├── Public Transit
│   ├── HOV Passenger Vehicle (3)
│   └── SOV Passenger Vehicle (1)
└── Inter-city (Air)
```

**Passenger Vehicles**
- Existing Vehicles
- New Vehicles

**Public Transit**
- Rapid Transit
- Bus

**Vkt from cars or trucks**

**Gas and Diesel Motors**

**Gas and Diesel Fuel Service**

**Vehicle Gas and Diesel Fuel Service**

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# Algorithm for new stock purchase

LCC

$$MS_j = \frac{\left(CC_j \cdot CRF_j + OC_j + EC_j + i_j\right)^{-v}}{\sum\left(CC_k \cdot CRF_k + OC_k + EC_k + i_k\right)^{-v}}$$

$$CRF_j = \frac{r}{1-(1+r)^{-n_j}}$$

Three key behavioural parameters:

- **Discount rate (r)** - time preference as reflected in actual decisions, excluding technology-specific risks

- **Intangible cost (i)** – technology-specific decision factors, especially differences in quality of service and cost risks

- **Market heterogeneity (v)** – reflects the diversity among decision makers in terms of real and perceived costs

# V - parameter and market heterogeneity



Point where Tech A is 15% cheaper than Tech B
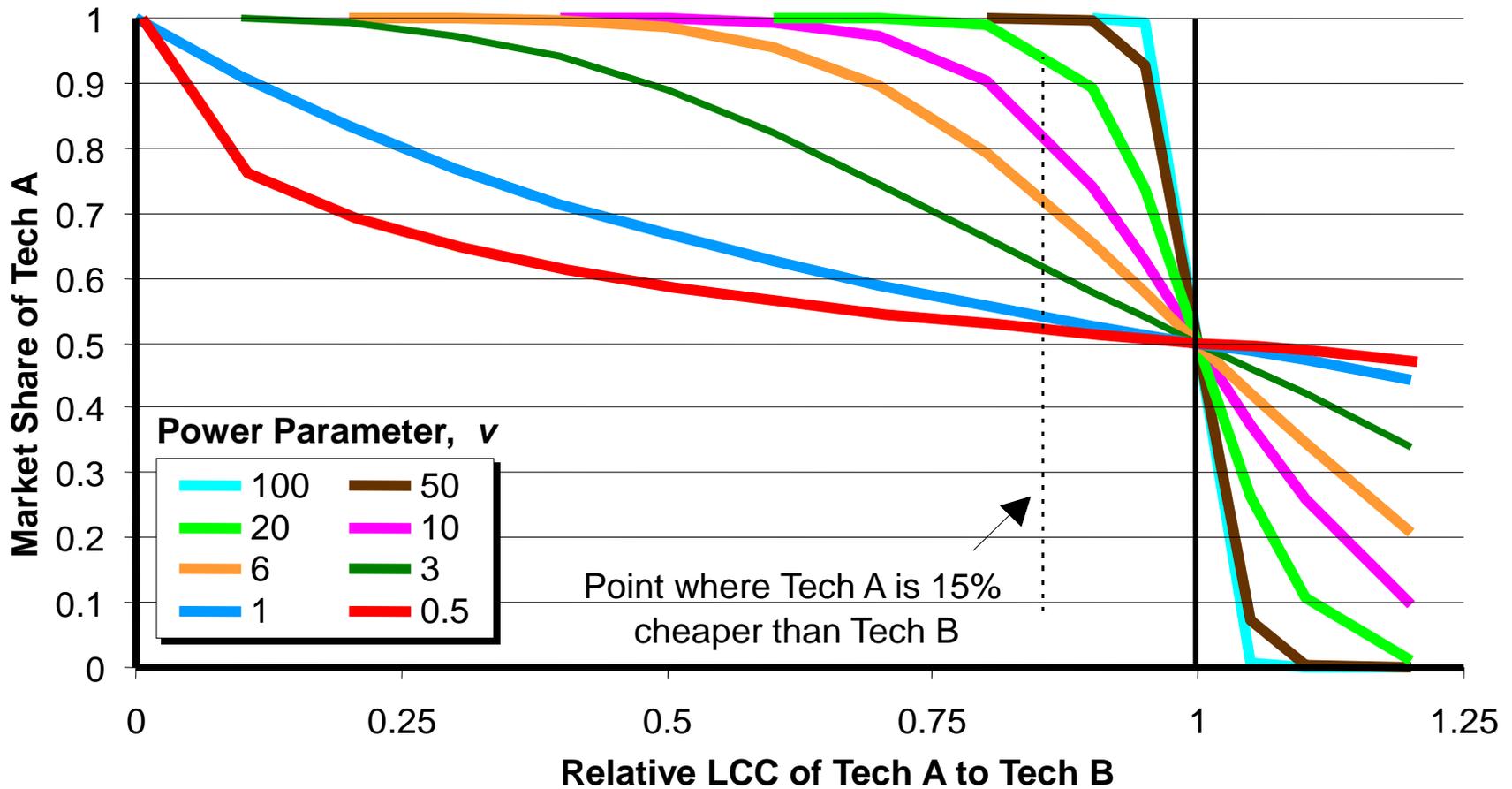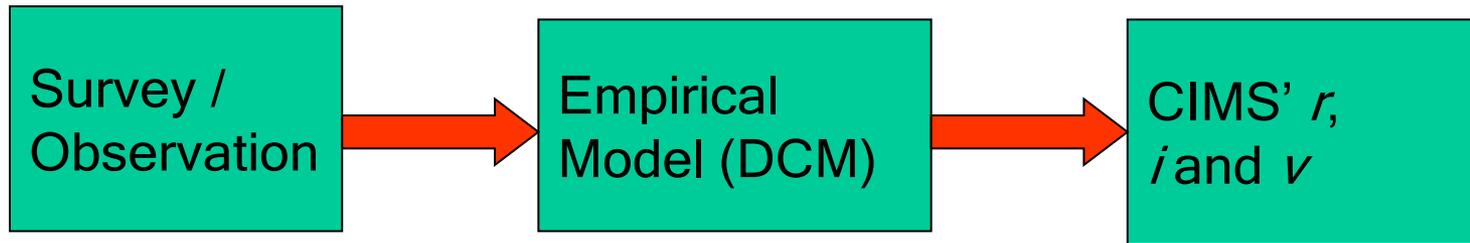
# Estimation of behavioural parameters

Two decades ago, we used literature review, calibration over recent past, and expert judgement to set behavioral parameters (v, i, r).

Over a decade ago, we initiated discrete choice surveys to estimate these parameters for key technology competitions, such as:

- transport mode choice (transit, bus, bike, SOV, HOV),

- vehicle choice (efficiency, fuel, motor type)

- industrial boilers and CHP,

- commercial and residential building insulation and HVAC.

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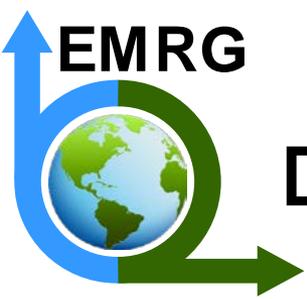
# Discrete choice models to estimate r, i and v

| Survey / Observation | → | Empirical Model (DCM) | → | CIMS' *r*, *i* and *v* |
|---|---|---|---|---|

Standard discrete choice model for technology choice surveys

$$U_j = \beta_j + \beta_{CC}CC + \beta_{OC}OC + \beta_{EC}EC + e_j$$

$$\beta_{AC} = \beta_{OC} + \beta_{EC} \qquad r = \frac{\beta_{CC}}{\beta_{AC}} \qquad i_j = \frac{\beta_j}{\beta_{AC}}$$

*v* = use OLS to estimate v for which predictions from CIMS are consistent with those from the DCM model (error term size vs betas.

Horne, Jaccard, Tiedemann (2005) "Improving Behavioral Realism in Hybrid Energy-Economy Models Using Discrete Choice Studies of Personal Transportation Decisions," Energy Economics, V27.

# Earlier estimates from Canada surveys

Discount rates from discrete choice studies

| Study | Implicit discount rate (%) |
|---|---|
| Choice of vehicle types | 22.6 |
| Choice of commuting mode types | N/A |
| Choice of home renovation | 26.3 |
| Choice of home heating system | 9.0 |
| Choice of industrial steam generation system | 34.7 |

Rivers, Jaccard (2006) "Useful models for simulating policies to induce technological change," Energy Policy,

# Technology cost dynamics

**Declining capital cost function: progress ratio**

- Links a technology's financial cost in future periods to its cumulative production
- Reflects economies-of-learning and economies-of-scale
- Parameters estimated from literature

Technology-specific progress ratios (PR) determine the extent to which capital cost declines for new technologies with cumulative production (N).

$$CC(t) = CC(0)\left(\frac{N(t)}{N(0)}\right)^{\log_2(PR)}$$

# Preference (intangible cost) dynamics

**Declining intangible cost function: neighbor effect**

- – Links the intangible costs of a technology in a given period (i) with its market share (MS) in the previous period
- – Reflects improved availability of information and decreased perceptions of risk – the "neighbor effect"
- – Estimated from discrete choice surveys that include info on decision maker (income, attitudes to technology risk, environmental attitudes, etc.)

$$i(t) = \frac{i(0)}{1 + Ae^{k*MS_{t-1}}}$$

Mau, Eyzaguirre, Jaccard, Collins-Dodd, and Tiedemann (2008) "The neighbor effect: simulating dynamics in consumer preferences for new vehicle technologies." Ecological Economics, V68.
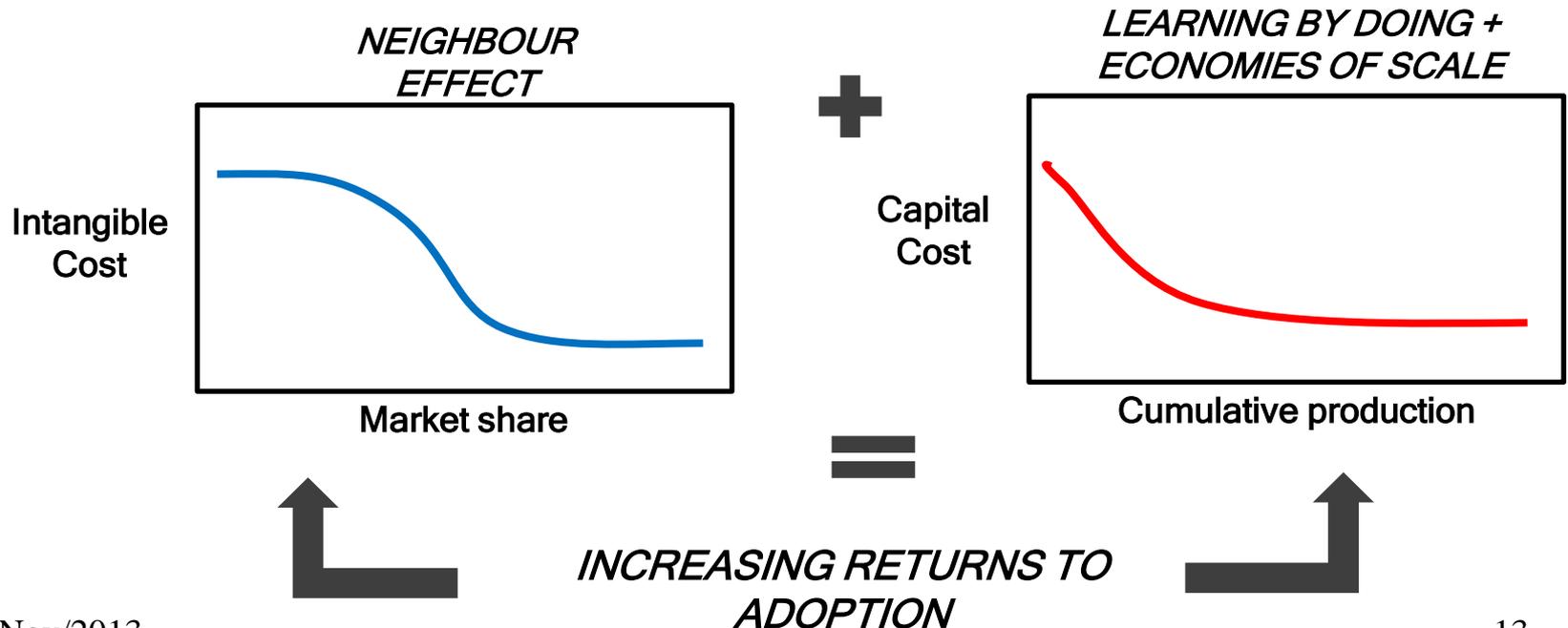
# Combined effect

Two key endogenous equations produce increasing returns to adoption:

- Declining intangible costs
- Declining capital costs

Increasing returns to adoption: ↑**users** leads to ↑**consumer acceptance** for a given technology



NEIGHBOUR EFFECT

Intangible Cost

Market share

**+**

LEARNING BY DOING + ECONOMIES OF SCALE

Capital Cost

Cumulative production

**=**

INCREASING RETURNS TO ADOPTION

# Joint model: stated and revealed preferences

Stated preference (SP) with new techs may be unreliable because of "hypothetical bias," (future choices with future technologies and fuels)
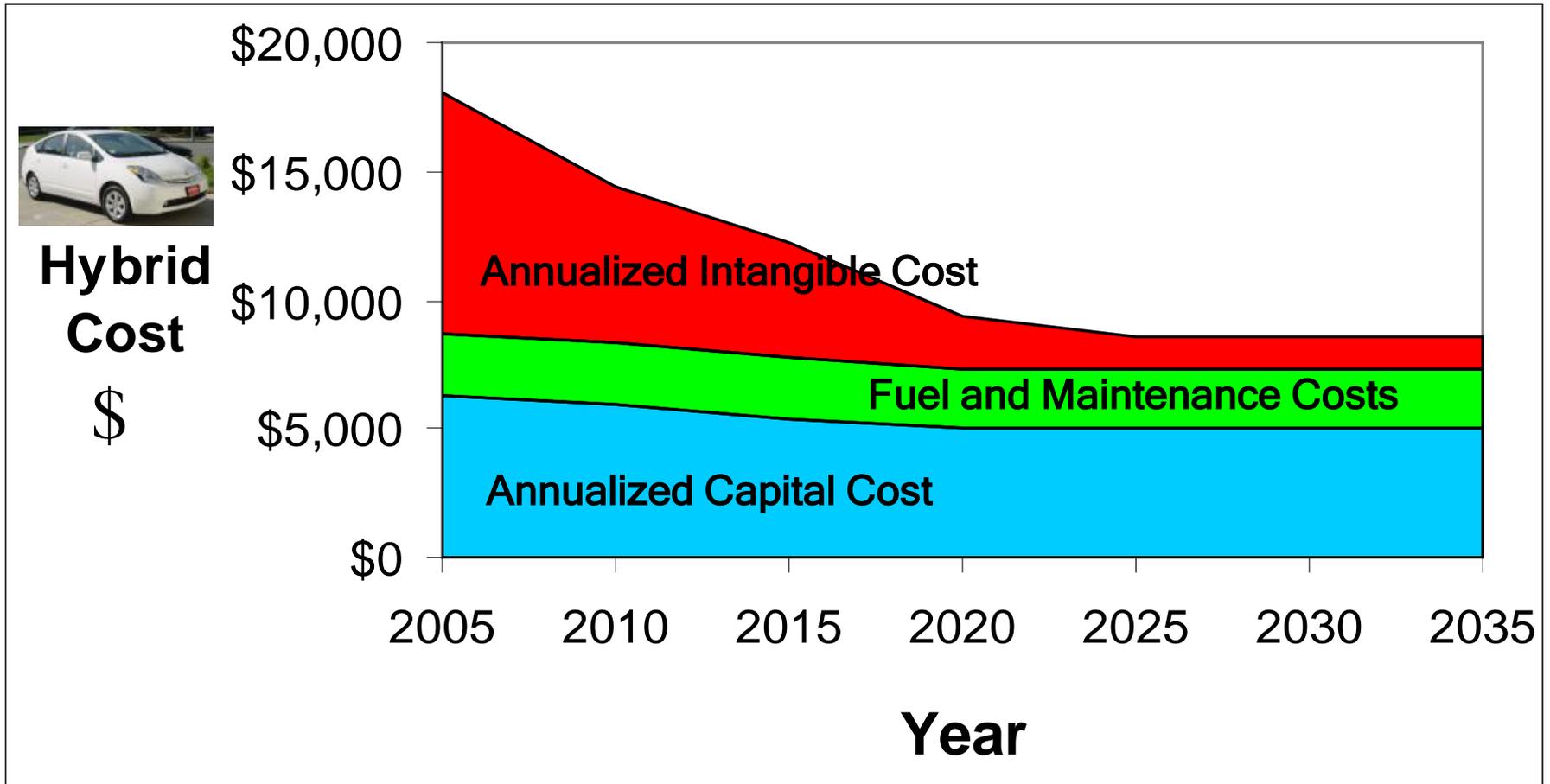
We combined SP and revealed preference (RP) evidence by surveying car buyers in Canada and California (n=966).

RP enabled comparison of real world preference differences between the two markets while SP discrete choice survey estimated likely preference change (falling intangible cost with greater market share).

Axsen, Mountain, and Jaccard (2009) "Combining stated and revealed choice research to simulate preference dynamics: the case of hybrid-electric vehicles." Resource and Energy Economics, V31(3).
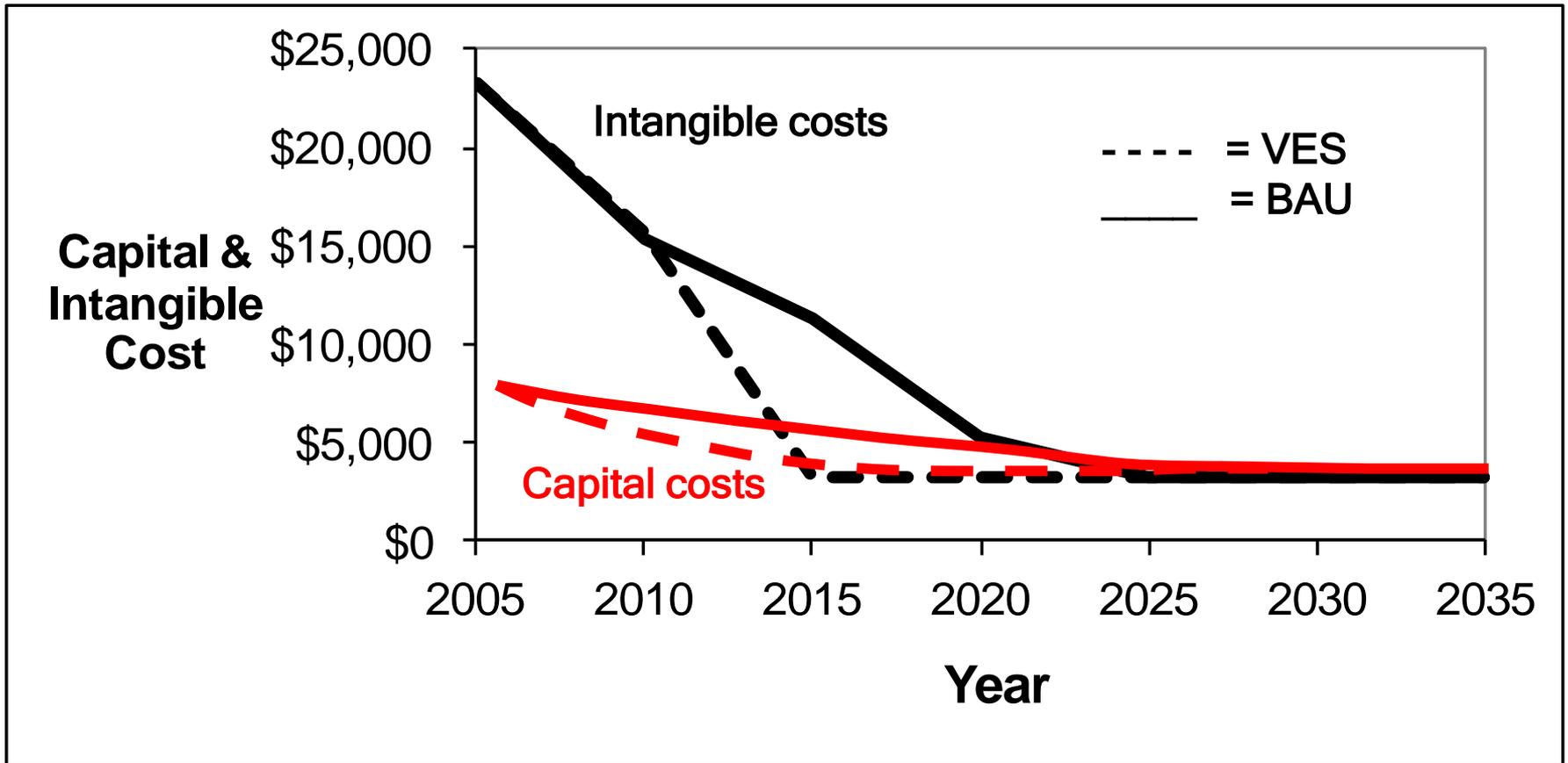
# CIMS-US simulation with combined learning curve and neighbor effect: BAU run
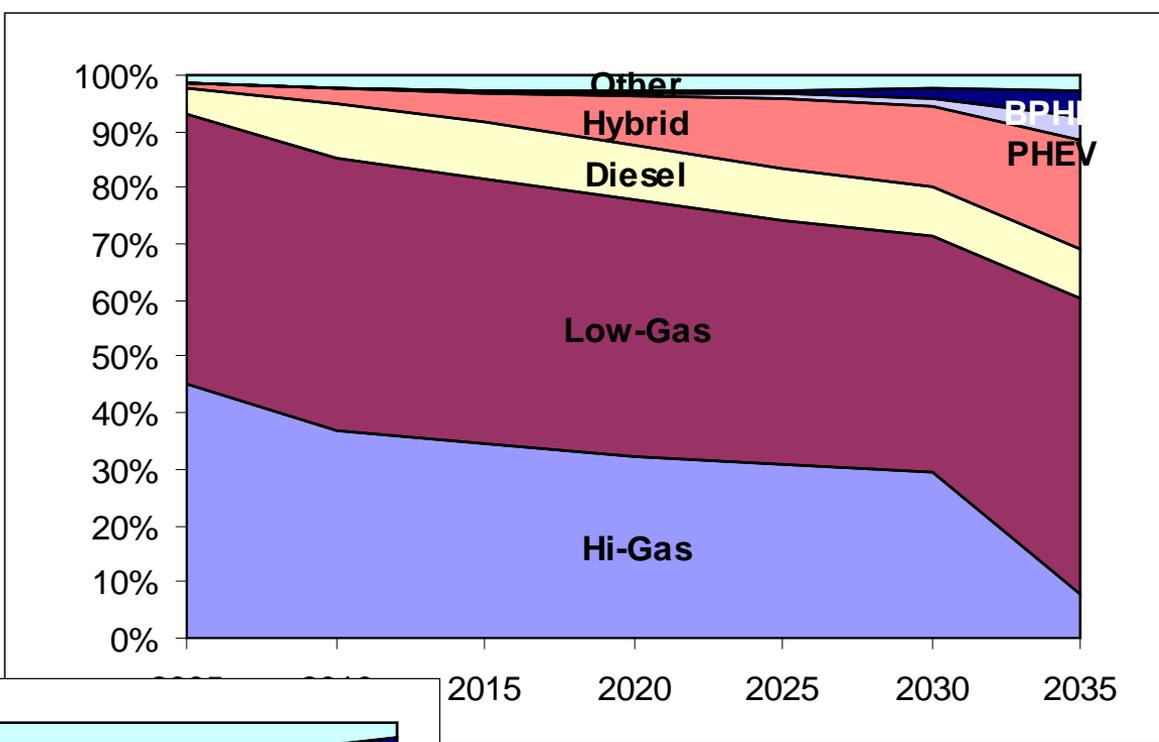
**Hybrid Cost**

$

Annualized Intangible Cost

Fuel and Maintenance Costs

Annualized Capital Cost

$20,000
$15,000
$10,000
$5,000
$0

2005  2010  2015  2020  2025  2030  2035

**Year**

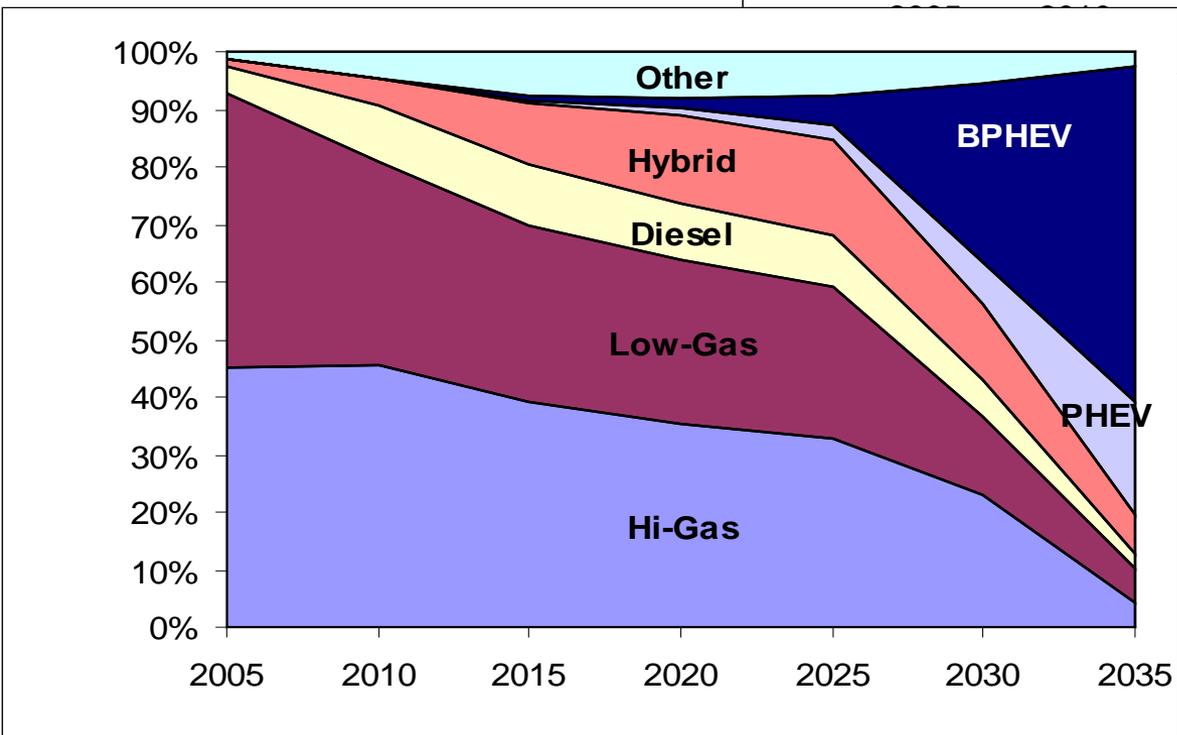Policy run: vehicle emission standard (VES) effect on capital and intangible costs

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# Combining VES with GHG pricing

BAU

$150 C-tax plus VES

# Discrete choice survey for commuter modal choice: response to policy

Hybrid model's choice function includes (at higher level) choice between transit, SOV, HOV, bike-walk, work-from-home.

Discrete choice survey in which we varied (1) total travel time, (2) transit wait time, (3) transit mode – metro, LRT, bus, (4) parking fees, (5) road pricing, (6) fuel costs, (7) faster HOV lanes.

We checked stated preferences (survey responses) against revealed preferences (similar urban areas) to check for hypothetical bias.

We later used these results for modeling with CIMS policies that changed urban form, urban density, transportation infrastructure and thus commuter travel distances.

Washbrook, Haider, Jaccard (2006) "Estimating Commuter Mode Choice: a Discrete Choice Analysis of the Impact of Road Pricing and Parking Charges," Transportation, V.33, 6.

*Table 1.* Attributes and attribute levels used in the discrete choice experiment.

| Driving alone | Carpooling | Taking express bus | |
|---|---|---|---|
| *In-vehicle travel time* | *In-vehicle travel time* | *In-express bus travel time* | |
| 1. +30% revealed time | 1. +15% revealed time | 1. +15% revealed time | |
| 2. +15% revealed time | 2. revealed time | 2. revealed time | |
| 3. revealed time | 3. −15% revealed time | 3. −15% revealed time | |
| 4. −15% revealed time | 4. −30% revealed time | 4. −30% revealed time | |
| *Road charge* | *Time spent picking up other carpoolers* | *Total time waiting for all buses* | |
| | | *walk to exchange* | *bus to exchange* |
| 1. $0 | 1. 3 min | 1. 3 min | 1. 5 min |
| 2. $1 | 2. 6 min | 2. 6 min | 2. 10 min |
| 3. $4 | 3. 9 min | 3. 9 min | 3. 15 min |
| 4. $9 | 4. 12 min | 4. 12 min | 4. 20 min |
| *Parking cost* | *Parking cost* | *Travel time from express bus stop to work* | |
| 1. $1 | 1. $0 | 1. 3 min walk | |
| 2. $3 | 2. $1 | 2. 6 min walk | |
| 3. $6 | 3. $2 | 3. 5 min local bus ride and 3 min walk | |
| 4. $9 | 4. $3 | 4. 10 min local bus ride and 3 min walk | |

# The needs of aggregate models
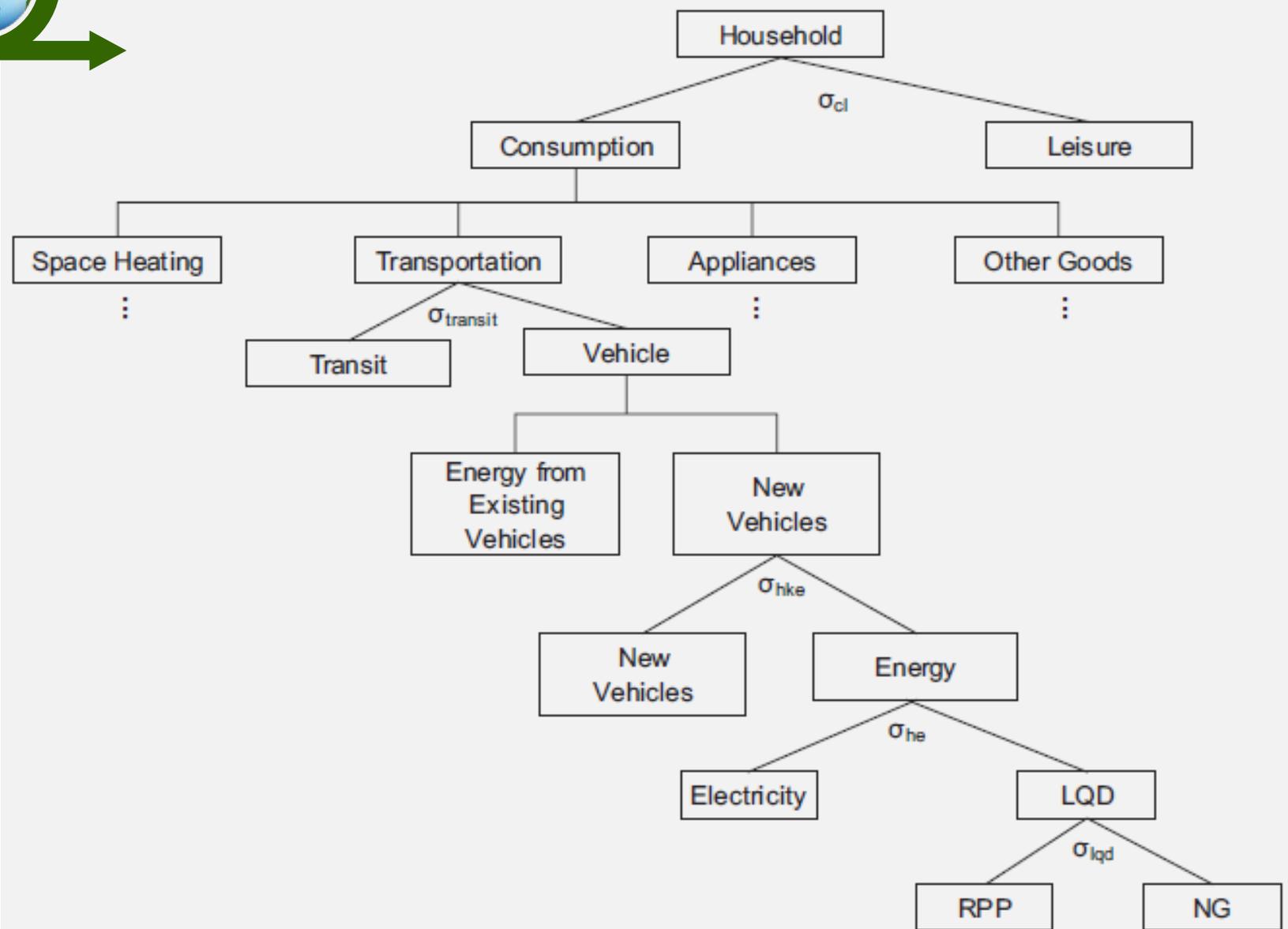
# Using a hybrid to estimate key parameters in aggregate models

Price-shock hybrid model to generate pseudo data for estimating parameters of production function (CES, Translog).

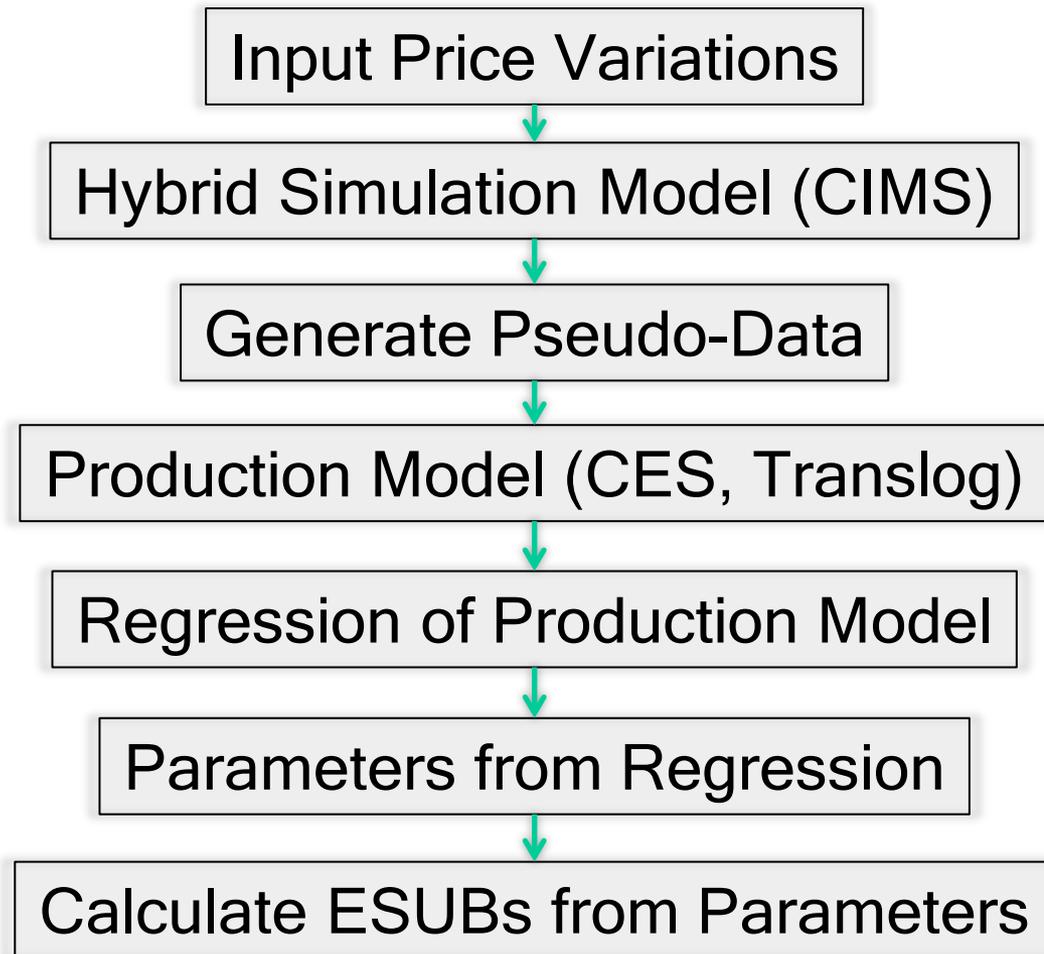Generate energy-capital inter-fuel elasticities of substitution (ESUBs) for CGE or other aggregate model.

Re-estimate ESUBs with alternative assumptions on (1) technological change, (2) cost change (fuel prices, emission charges), (3) preference changes, (4) infrastructure / urban form changes.

Provides "if-then" ESUBs, whose values are a function of policies targeted at transport investment / tech costs, preferences, and opportunities (access to transit, high density living, etc.).

E.g., Study for EPRI in 2013. "Down the isoquant: The potential for energy substitution in the US." Jaccard, Peters, and Goldberg, for Electric Power Research Institute.

# Estimating ESUBs for aggregate models

Input Price Variations

↓

Hybrid Simulation Model (CIMS)

↓

Generate Pseudo-Data

↓

Production Model (CES, Translog)

↓

Regression of Production Model

↓

Parameters from Regression

↓

Calculate ESUBs from Parameters

# Integrating urban form and infrastructure

## Table A4: Elasticities of substitution for households

| | $\sigma_{cl}$ | $\sigma$ transit | $\sigma$ hke | $\sigma$ he | $\sigma$ lqd |
|---|---|---|---|---|---|
| Space Heating | | 0 | 3.3 | 3.5 | 3.4 |
| Transportation | 0.6 | 0.2 | 0.6 | 7.5 | 0 |
| Appliances | | 0 | 0.1 | 0 | 0 |
| Other Goods | | 0.25 | 0 | 0 | 0 |

Source: CIMS, 2009 and Paltsev, 2005.

# Conclusion

Research on technology acquisition shows that non-financial preferences matter, especially with new technologies.

Research on policy shows the importance of detailed regulations on technologies and fuels.

Research on mobility demand and mode choice shows that urban form and other contextual factors matter.

We can empirically estimate key choice parameters in a hybrid model (such as CIMS) by using detailed tech acquisition data (revealed) and/or data from a targeted discrete choice survey (stated).

We can simulate hybrid models (such as CIMS) under different assumptions about preferences, prices and technologies to estimate ESUB parameters for aggregate models (such as IAMs)

# Extra slides
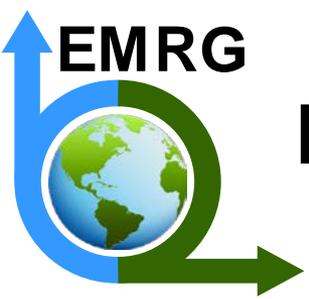
# Estimated declining intangible cost curve for hybrid electric vehicles (HEV)