Energy-economy modeling and behavioral realism:
How much is useful?

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Words of wisdom?

All models are wrong.

But some are more useful.

Energy-economy-climate analysts are like painters.

They tend to fall in love with their models.


Optimization Clinic
AUTOMATIC
CAUTION
DOOR
AUTOMATIC DOOR - STAND CLEAR
AUTOMATIC DOOR - STAND CLEAR
URGENT CARE
CHILDRENS CLINIC
LOCATED HERE
We ALL need
to remember
to clean
our hands!
PLEASE
TAKE A
NUMBER
AND THEN
HAVE A
SEAT.

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Inside the optimization modelers' clinic

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Inside the simulation modelers' clinic

Key messages?

Make your model useful – and keep reforming it as the critical issues and questions change.

Avoid falling in love – be willing to change models if your model is not useful for the next critical questions.

Beware a lifetime devoted to pure optimization. Otherwise . . .

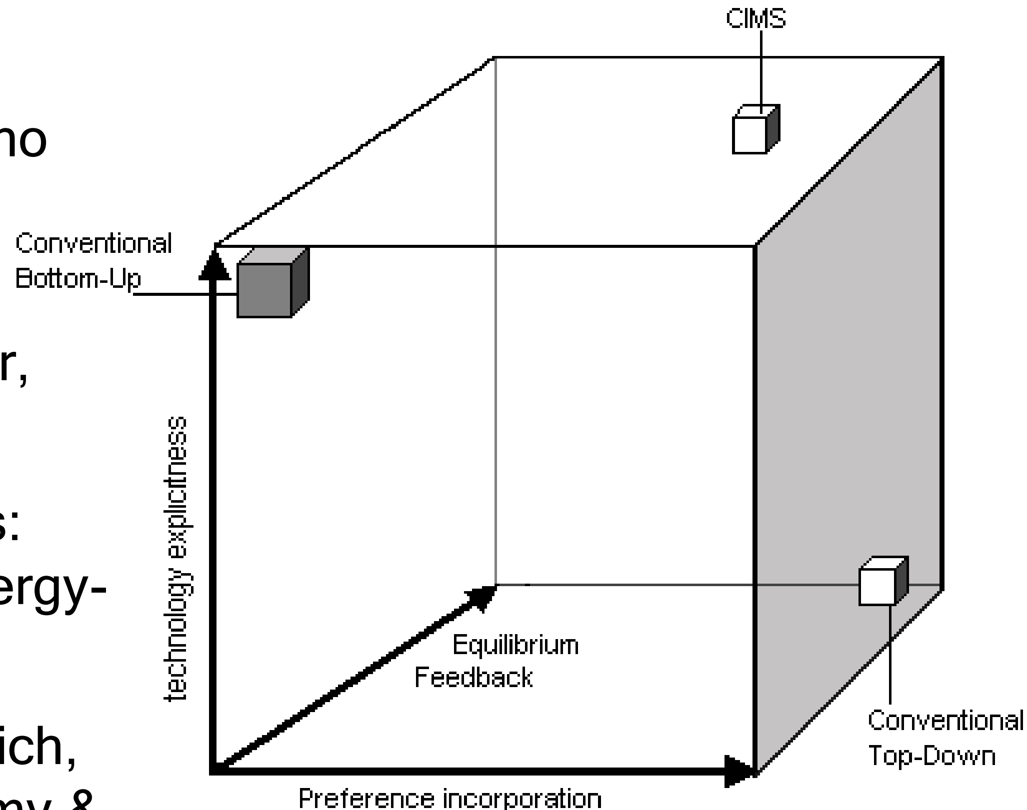
Ancient history: top-down vs. bottom-up

Conv. “top-down” econ models: no technology, simple behavior.

Conv. “bottom-up” spreadsheet models: tech-rich, naïve behavior, extreme partial equilibrium.

Optimization “bottom-up” models: tech-rich, naïve behavior, full energy-economy equilibrium.

Hybrid simulation models: tech-rich, behavioral, some energy-economy & macro-economy equilibrium.



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: a climate-energy policy simulation model for a specific jurisdiction

Typical tech-rich model:

- Explicit tech details (cost, lifespan, efficiency, fuel)
- Semi-endogenous retirement of old stock (time, cost)
- Semi-endogenous service demand (growth, cost)
- Exogenous industrial structure (external forecast)
- Semi-endogenous structural change (macro elasticities)

Hybrid in having endogenous micro-econ simulation of new and retrofit tech choices and thus energy supply-demand, especially domestic

CIMS: why these design choices?

Useful to policy-makers in one (or a few) jurisdiction(s) assessing whether their policies would re-direct the energy-economy system to a low emission path. (NEMS-US, CIMS-Canada.)

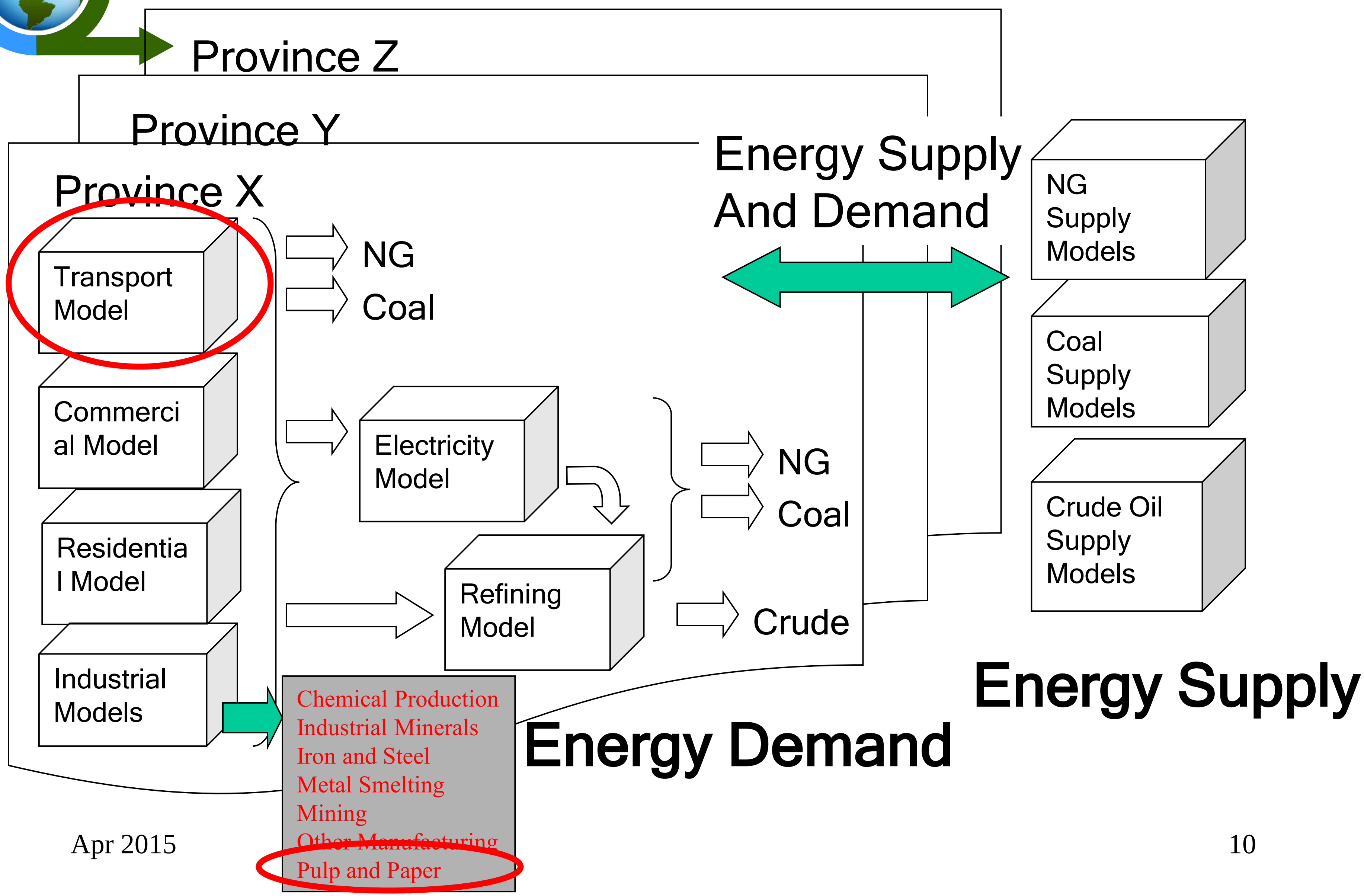
Equally important (!) – useful in exposing "faking it" policies (information, subsidies, soft regs). A counter to climate policy delusions.

However, less or not-at-all useful for:

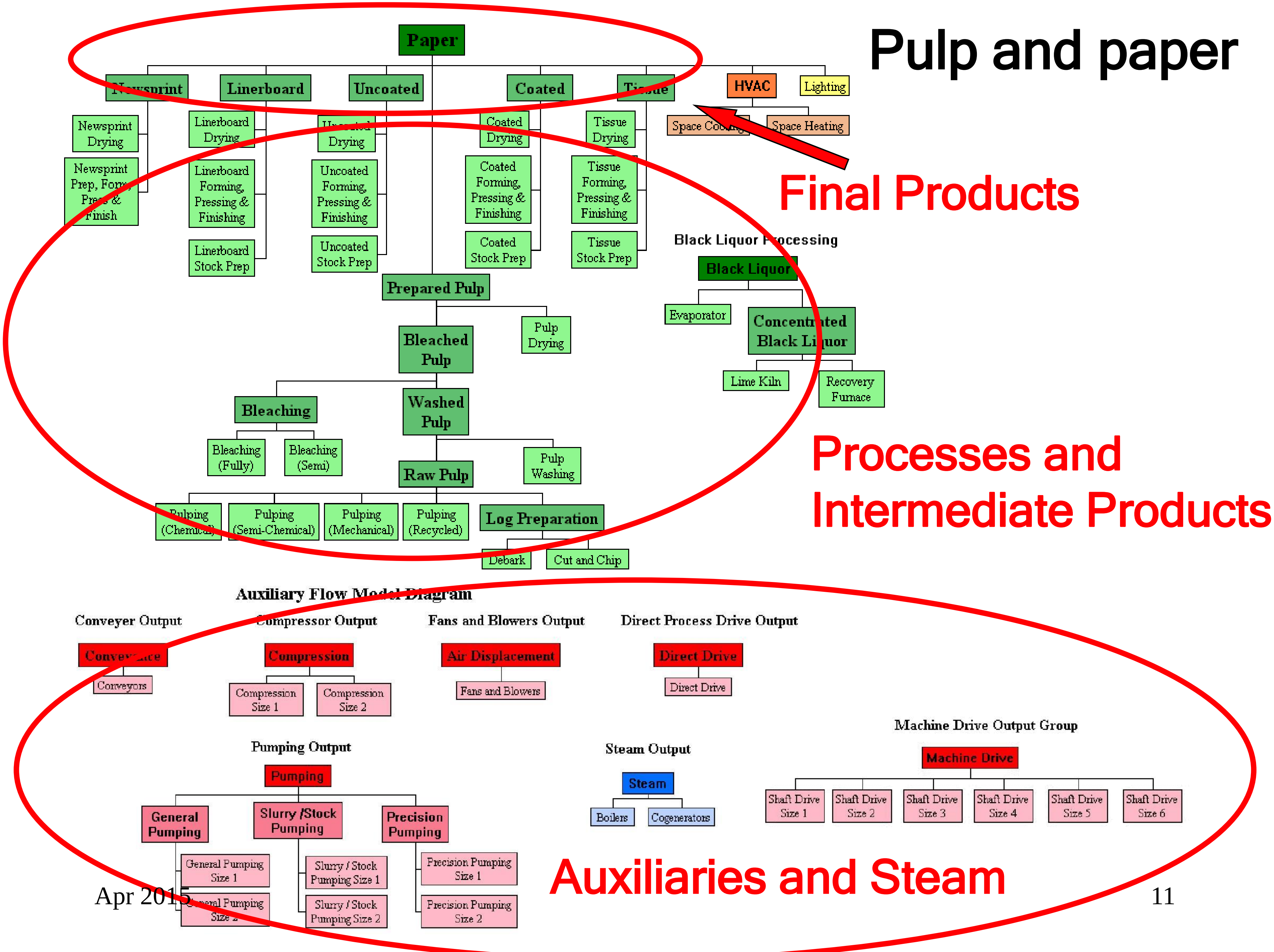
- Spatial policies (urban form, transit)
- Redistributive, welfare and competitive impacts.
- Simulating multi-jurisdictional efforts and global energy markets

I'll next explain behavioral realism in CIMS, and then efforts to go beyond CIMS to achieve other "usefulness" objectives.

CIMS: standard model structure



Pulp and paper



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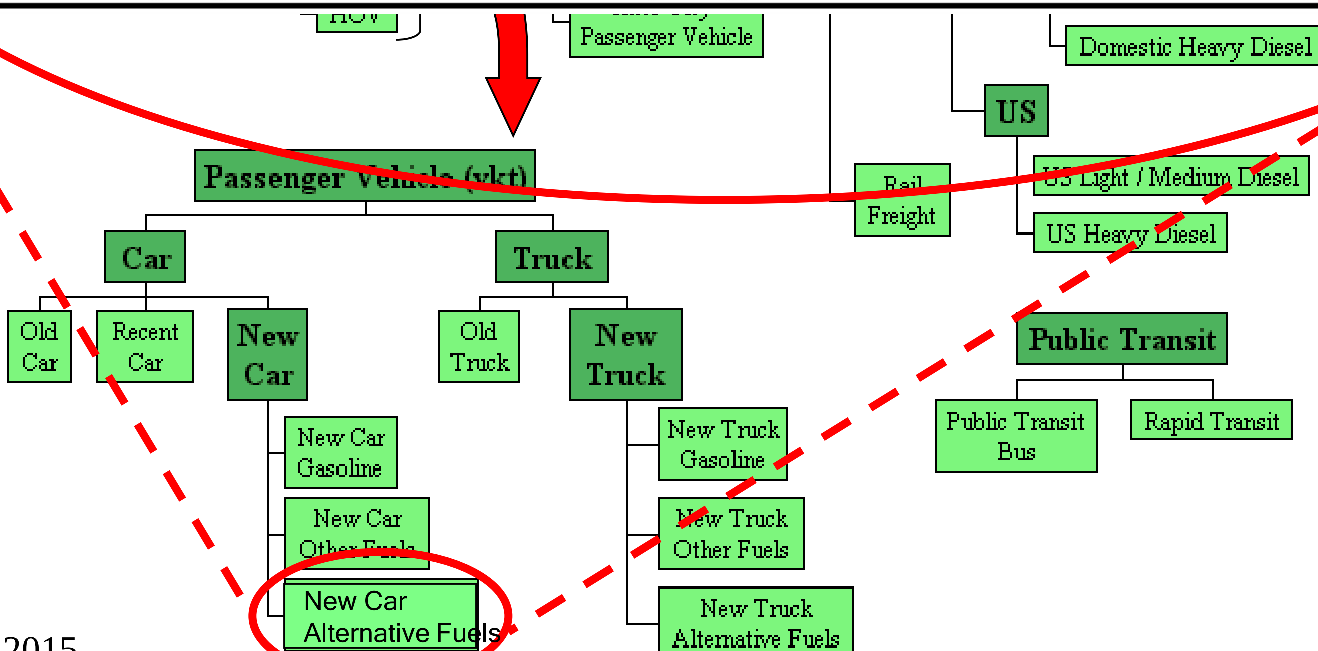
Transport

Technology	Capital Cost	Fuel Type	Fuel Consumption	Direct CO2 Emissions
Ethanol	$25,511	85/15 Eth/Gas	0.0034 GJ/km	0.049 kg/km
Methanol	$26,300	85/15 Meth/Gas	0.0034 GJ/km	0.195 kg/km
Hybrid	$29,000	Gasoline	0.0016 GJ/km	0.109 kg/km
Battery Electric	$48,500	Electricity	0.0011 GJ/km	0 kg/km
Fuel Cell (H2)	$140,000	Hydrogen	0.0023 GJ/km	0 kg/km



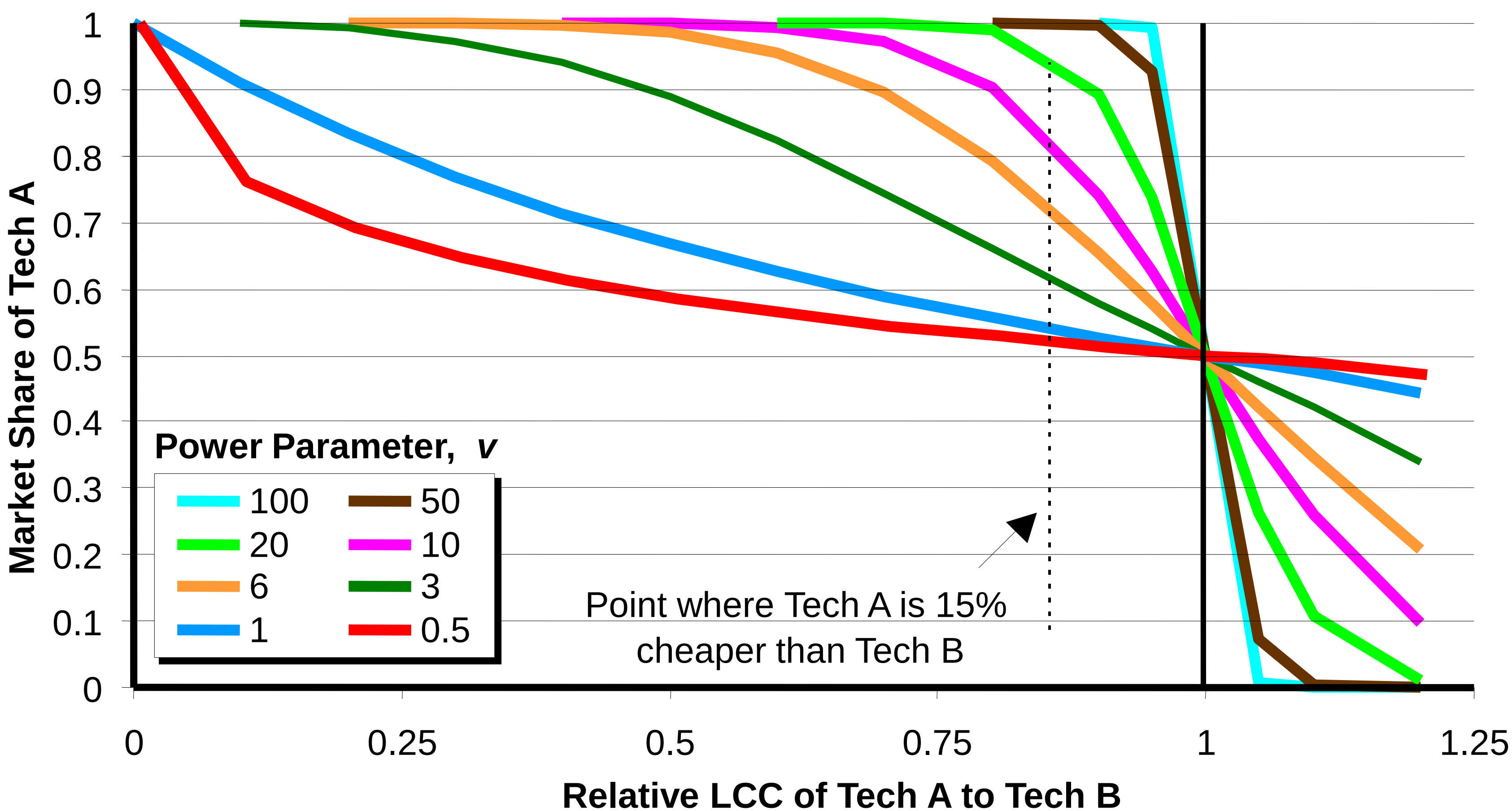
Key behavioral parameters for new & retrofit tech choices

$$MS_j = \frac{\overbrace{\left(CC_j \cdot CRF_j + OC_j + EC_j + i_j\right)}^{\text{LCC}}{}^{-v}}{\sum \left(CC_k \cdot CRF_k + OC_k + EC_k + i_k\right)^{-v}} \qquad CRF_j = \frac{r}{1-(1+r)^{-n_j}}$$

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 (logistic curve)

V - parameter reflects market heterogeneity



Behavioural parameter estimation

15 years ago, we began discrete choice surveys to estimate the three behavioral parameters. This included stated and revealed preference studies in:

- transport mode choice (transit, bus, bike, walking, vehicles),
- vehicle choice (efficiency, fuel, motor type)
- industrial boilers and cogeneration,
- commercial and residential building insulation and HVAC.

Increasingly, we focused on cost and non-cost dynamics on technology choices, summarized by “the neighbor effect.”

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

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

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

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.

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Earlier (i) estimates from Canada-US 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,

We use a standard learning curve for capital cost (cc)

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 taken from literature

Thus, technology-specific progress ratios (PR) determines the capital cost decline with cumulative production (N).

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

We combine this with a market-share sensitive function for intangible cost (i)

Declining intangible cost function: neighbor effect

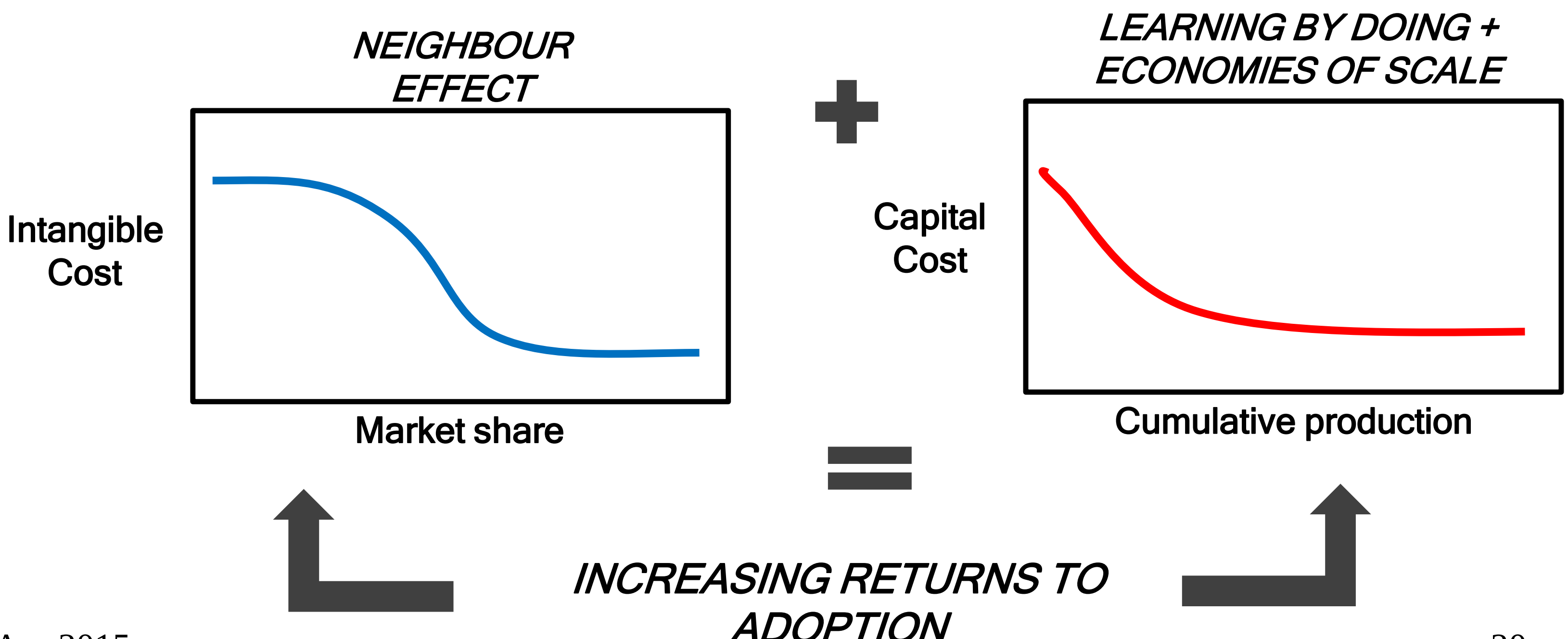
- Links the intangible costs of a technology in a given period (i) with its market share (MS) in the previous period
- Reflects improved availability of information and decreased perceptions of risk with rising market share
- Estimated from discrete choice surveys that include info on decision maker (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.

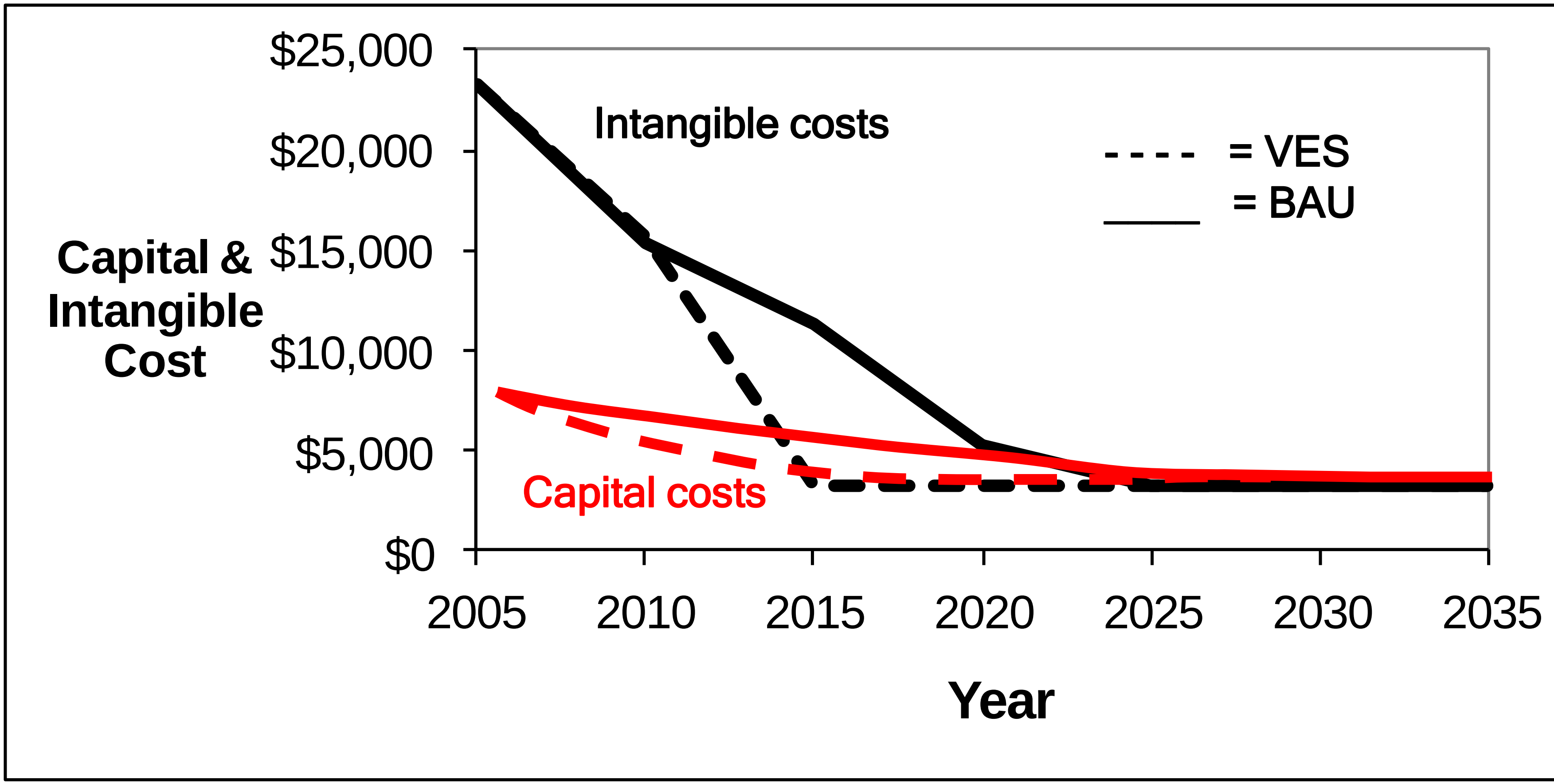
Combined effect: cost-adoption dynamic

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



CIMS-US policy simulation with combined capital and intangible cost feedbacks

- VES – vehicle emission standard (ULEV / ZEV)
- capital and intangible costs are annualized for plug-in hybrid



Other useful models needed: urban form

As noted, CIMS is not spatial. In an urban setting, we know that preferences depend in part on urban form (density nodes, mixed land-use, ease of access to alternative mobility options)

QUEST project. CIMS used in soft-linking mode with (1) GIS-based model for urban land-use and (2) urban transportation model.

Behavioral estimates about location and mobility choices from the urban form and transportation literature, while CIMS simulates technology choices. Combined heat and power often set exogenously.

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Other useful models needed: macro-economic

Elasticities of substitution (K-E, interfuel) in CGE models are often based on historical data when we know that these must differ in future as new tech-fuel options develop, such as PHEVs.

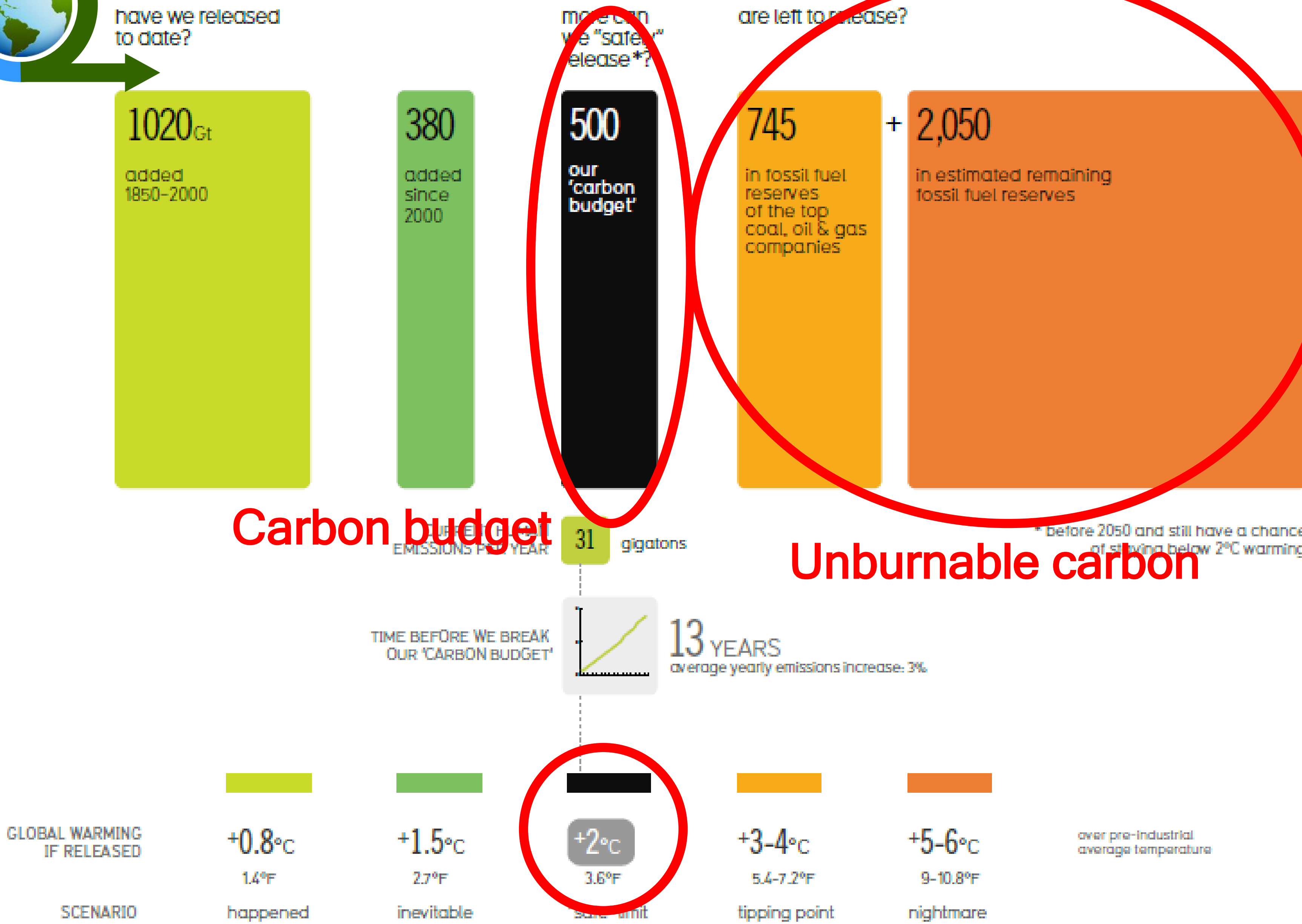
We simulate CIMS for future decades with a complete range of price shocks to estimate ESUB values, and use these in a CGE.

Recent study in Canada of regional GDP impacts of different carbon pricing and revenue recycling policies with CIMS+CGE.

Recent study for EPRI using CIMS-US to estimate ESUB values for its CGE model.

In both cases we found smaller E-K and larger interfuel ESUBs than those estimated from historical data.

Other useful models: 2 C and FF projects



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Other useful models needed: IAMs

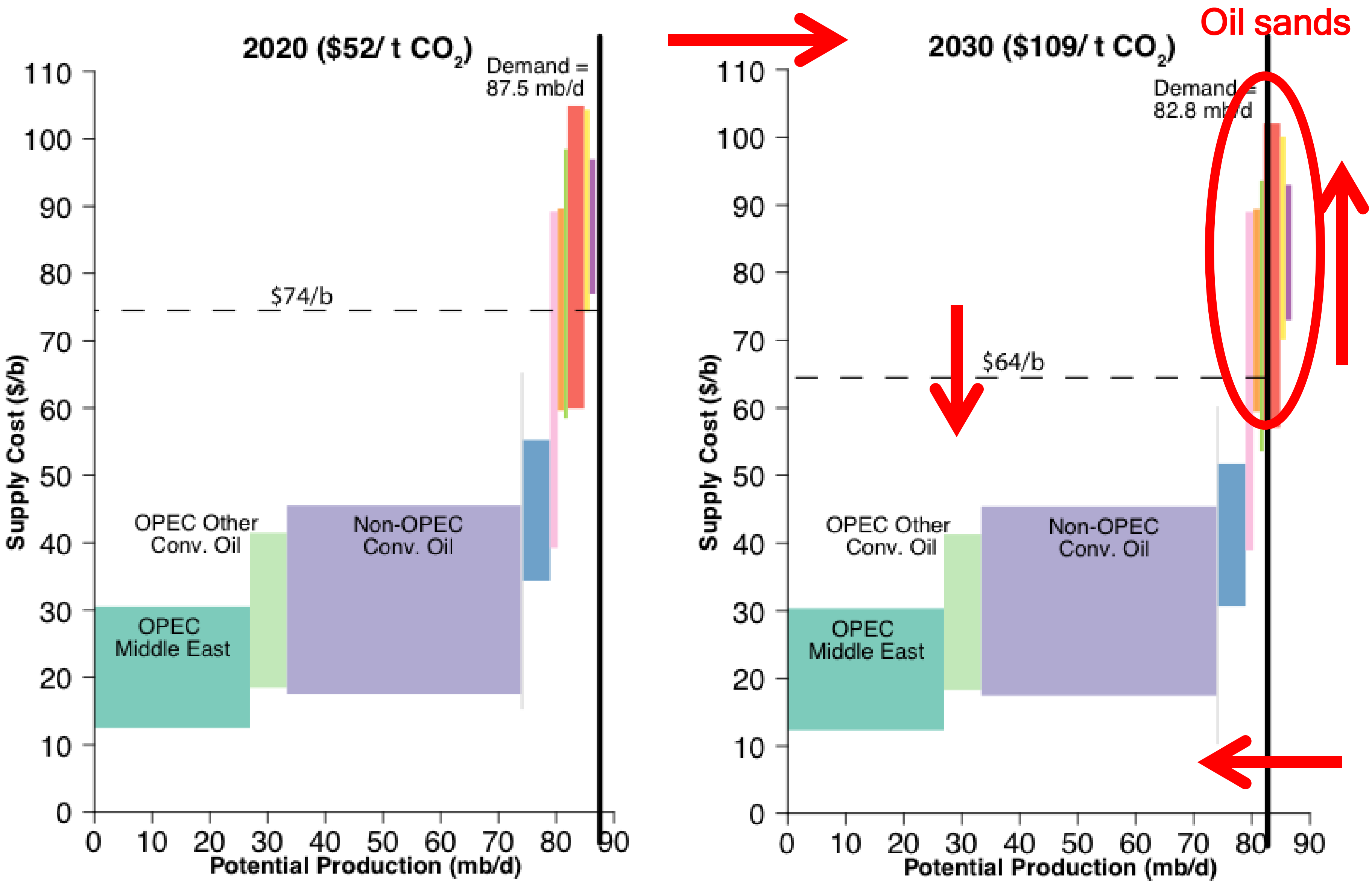
The 2 C target, the resulting carbon budget, and the problem of delusion. Every fossil fuel project claims to be within the budget.

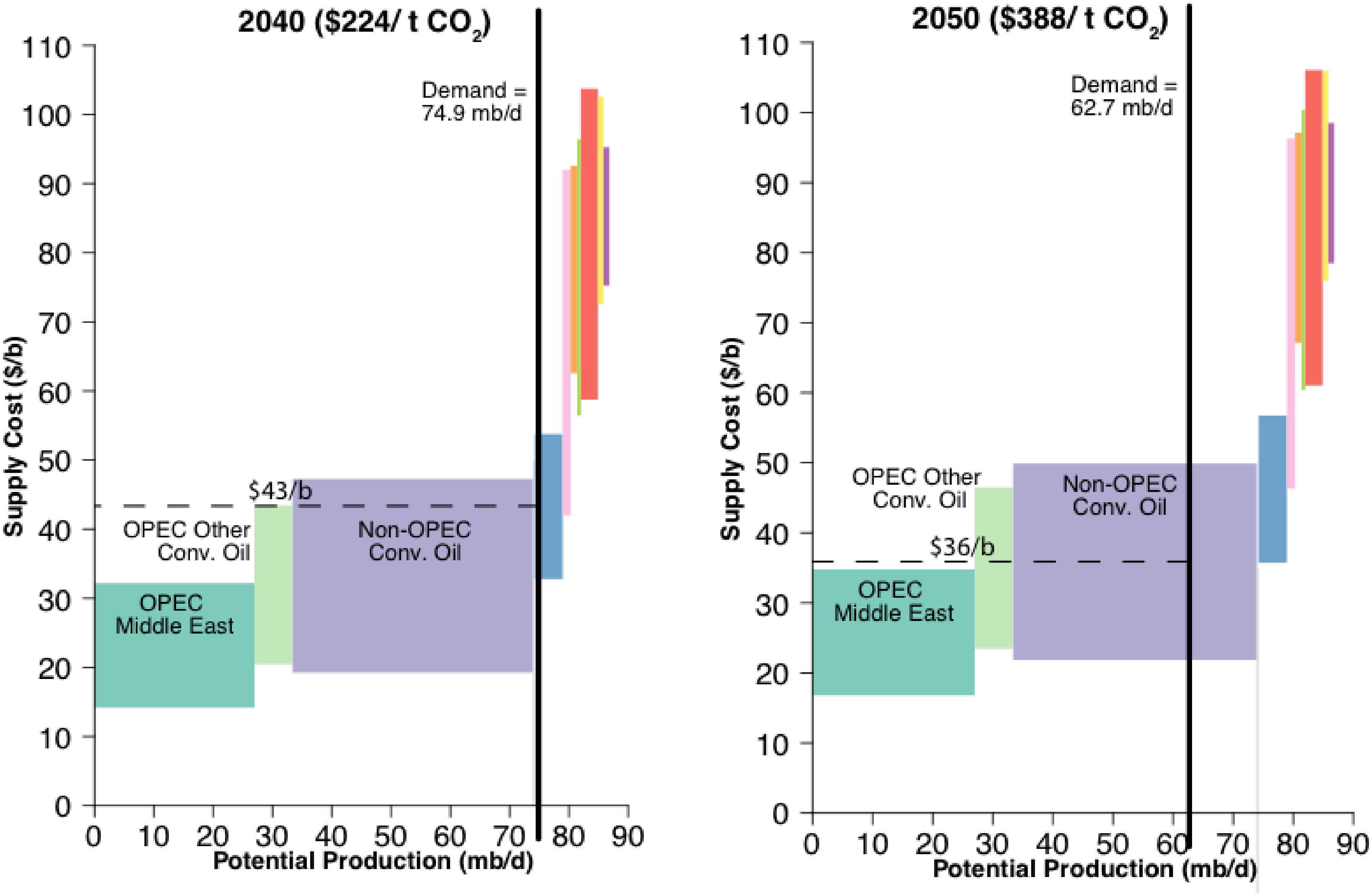
CIMS is not global. Does not simulate global oil price. We need this price from the global energy-economy-emission models.

We ask global modelers to tell us the oil price in 2050. Answers are almost always above $50 / barrel. (Something to do with foresight and assumptions about scarcity perhaps.)

Yet new Canadian oil sands and other unconventional oil will develop at that price, even with the upward pressure on production costs from a high carbon price ($400/tCO2?).

Our latest work surveys major modeling groups for their 2 C estimates of carbon prices and oil demand, and from that we try to estimate our own oil price for use in project approval in NA.


2020 ($52/ t CO_2)
Demand = 87.5 mb/d
$74/b
OPEC Other Conv. Oil
Non-OPEC Conv. Oil
OPEC Middle East
Supply Cost ($/b)
Potential Production (mb/d)
2030 ($109/ t CO_2)
Oil sands
Demand = 82.8 mb/d
$64/b
OPEC Other Conv. Oil
Non-OPEC Conv. Oil
OPEC Middle East
Supply Cost ($/b)
Potential Production (mb/d)


2040 ($224/ t CO_2)
Demand = 74.9 mb/d
$43/b
OPEC Other Conv. Oil
Non-OPEC Conv. Oil
OPEC Middle East
Supply Cost ($/b)
Potential Production (mb/d)
2050 ($388/ t CO_2)
Demand = 62.7 mb/d
$36/b
OPEC Other Conv. Oil
Non-OPEC Conv. Oil
OPEC Middle East
Supply Cost ($/b)
Potential Production (mb/d)

Can optimization models simulate behavior?

Yes. But how realistically? And on what empirical basis?
intangible costs? (i)
different time preferences? (r)
winner-takes-all? (v)

I look forward to hearing about the innovations in behavioral modeling at this workshop. And remember, . . .

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Thank you.

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