Efficiency vs Other GHG Abatement Actions: Policy Implications

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Talk Outline

I. Debates in estimating the cost and achievable potential of energy efficiency.

II. Using an energy-economy model to explain and assess cost estimates of energy efficiency and GHG abatement.

III. Using an energy-economy model to estimate contributions of efficiency and other GHG abatement options under alternative targets and policies.

Reminder: actions and policies for GHG abatement

Actions by households and firms

- Energy efficiency (if using fossil fuels)
- Fuel switching (away from fossil fuels)
- Emissions capture and storage
- "The rest" (industrial processes, landfill management, agriculture, forestry)

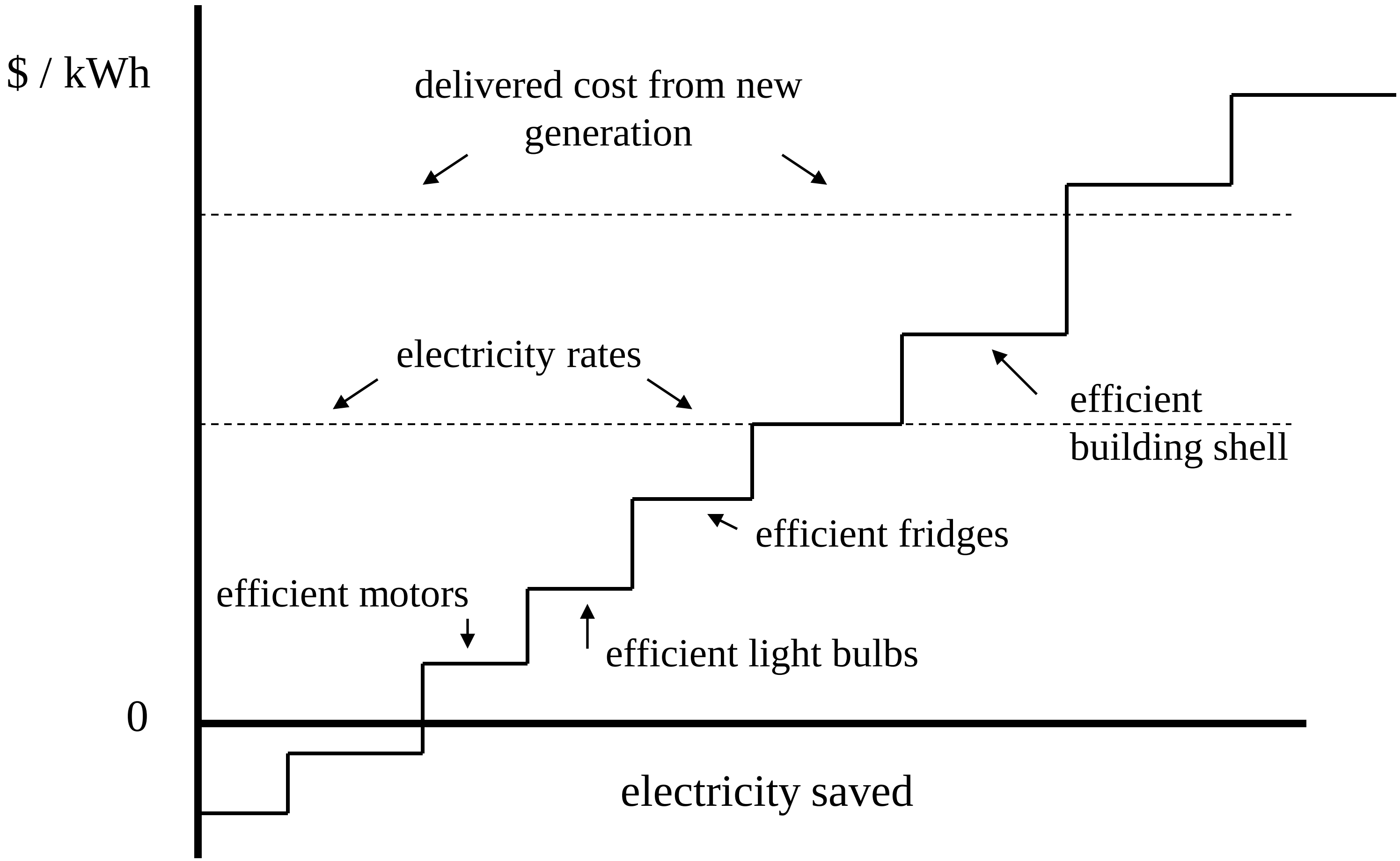
Policies by government to drive actions

- Information
- Subsidies
- Regulations - prescriptive
- Regulations - flexible (RPS, vehicle standards)
- Emissions charges (carbon tax, cap-and-trade)

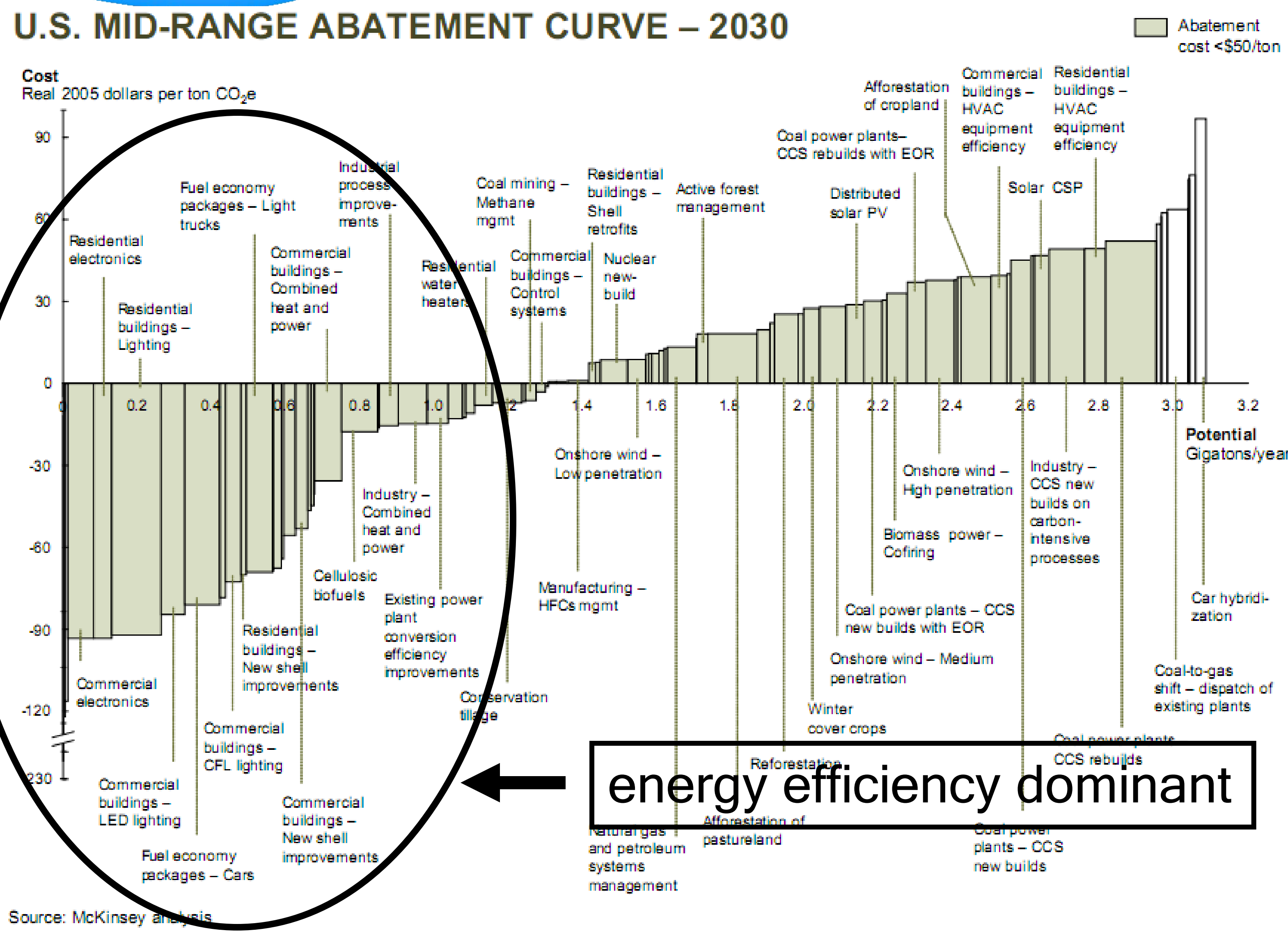
energy and materials research group

I. Debating efficiency cost curves: Déjà vu all over again

Energy efficiency cost curve



GHG abatement cost curve



Frequent conclusion

Since energy efficiency is profitable, focus on it first.

Being profitable, it can largely be achieved with non-compulsory information programs and subsidies (utility DSM), along with modest efficiency regulations.

These two assumptions have dominated real-world climate policy for over two decades.

However, . . .

While energy efficiency cost curves were already popular 30 years ago, they long ago fell out of favor with energy-economy modelers, who argued the curves mislead about costs and therefore policy implications.

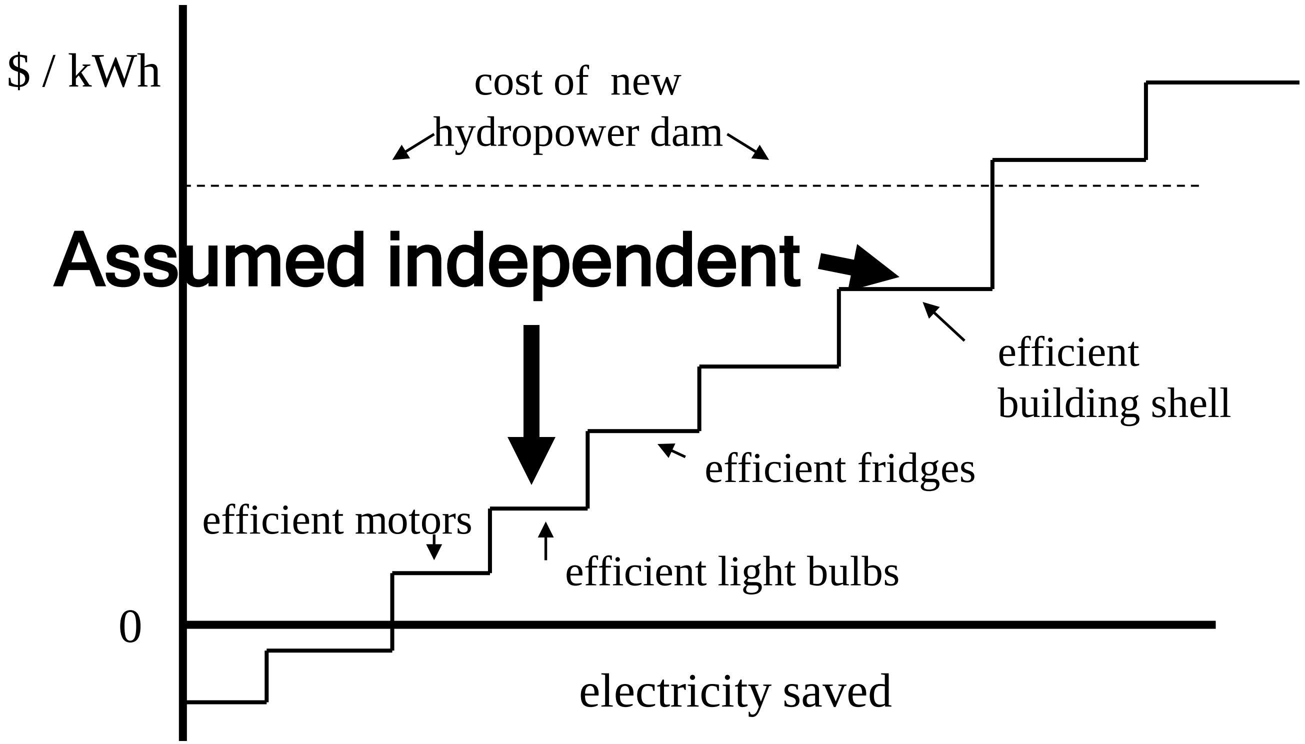
Three key problematic assumptions with cost curves:

- efficiency actions assumed independent,
- markets and actors assumed homogeneous,
- technologies assumed perfect substitutes

Issue #1
Actions assumed independent

Construction of cost curves implies that each action is completely independent of every other action. (extreme partial equilibrium analysis)

(1) demand-side, (2) supply-demand (price, rebound, GHG content), (3) structural change, income and GDP effects



Issue #2
Market conditions and participants assumed homogeneous

Market evidence shows that acquisition of a more efficient or lower emission technology will cost X for the first 20% of the market, X+Y for the next 20%, X+Y+Z for the next 20%, and so on.

Reasons include:

- different age of existing capital stock and hence cost of replacement at a particular time (reference case efficiency)
- local differences in transaction costs – learning, acquisition, installation and operation (heterogeneity of market actors)

Issue #3
Technologies assumed perfect substitutes

Quality of service assumed identical.

But some technologies provide (or are perceived to provide) lower quality service – a concern with new technologies especially (e.g., efficient light bulbs, transit vs personal vehicles)

Risk assumed identical.

But (1) long payback investments often higher investment risk, and (2) new technologies often higher failure risk.

Incorporating these risks usually causes higher “expected costs” for high efficiency / low emissions technologies.

Energy-economy modelers: response to cost curve "issues"

Construct integrated "hybrid" energy-economy models:

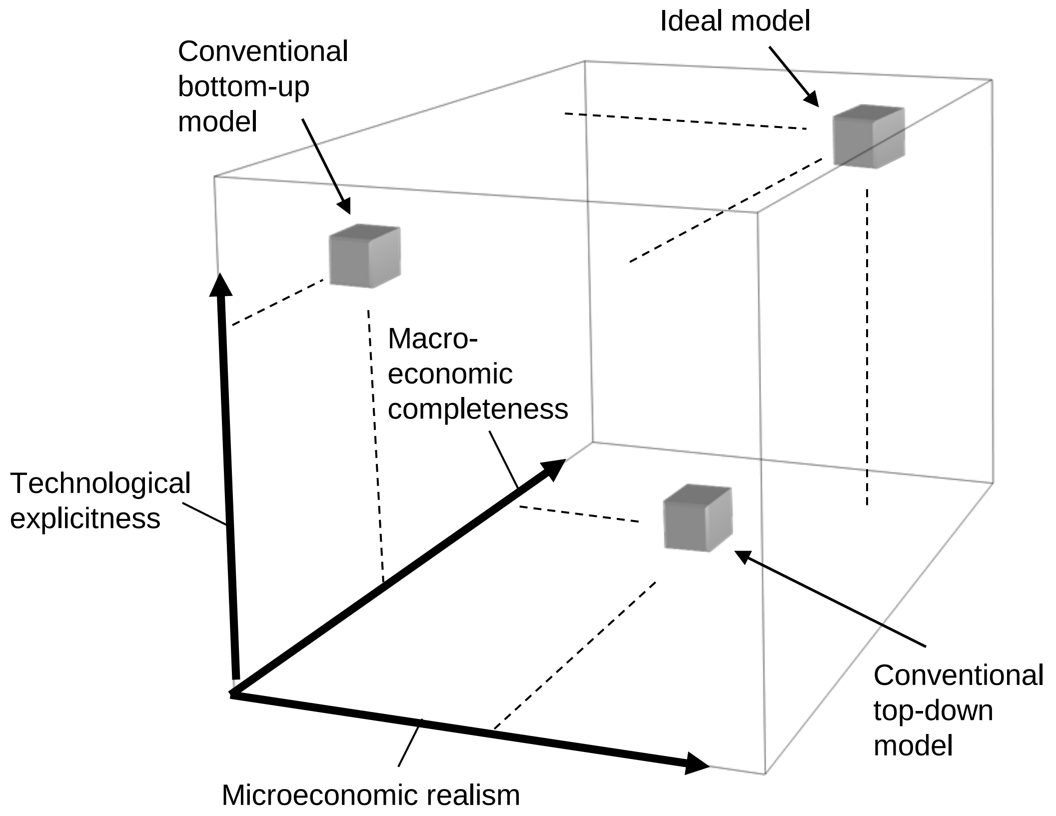
- integrate energy supply with energy demand
- integrate energy system with rest of economy

Track technology stock turnover (possibly explicit vintages)

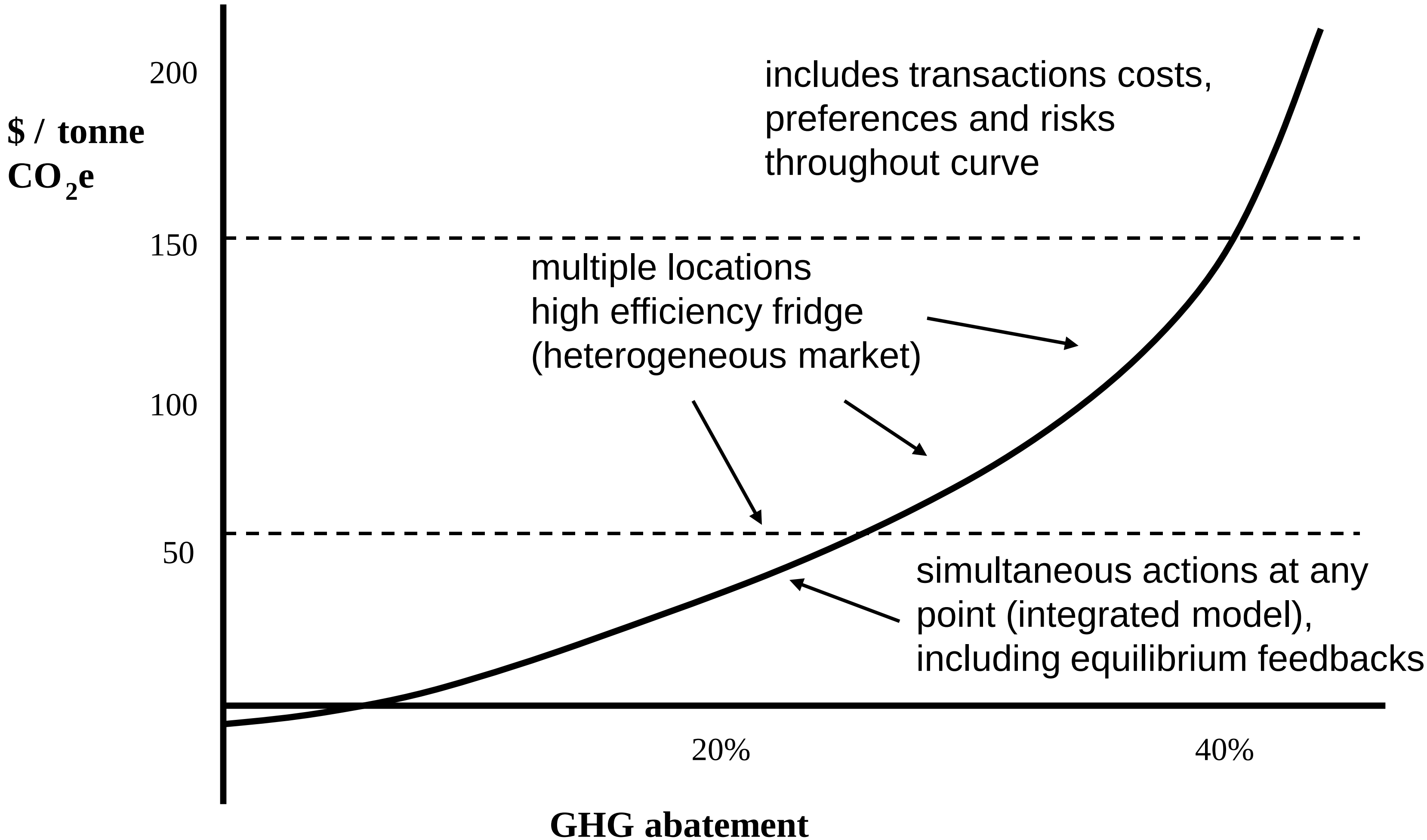
Estimate model behavioral parameters that explicitly or implicitly incorporate heterogeneous:

- time preferences of decision-makers
- non-financial values (preferences related to technology attributes)
- perceived and real differences in technology risk

Typology of energy-economy models:



Hybrid energy-economy model: estimating CO_2 MAC curves



II. Using a hybrid energy-economy model to explain and assess cost estimates of energy efficiency and GHG abatement (from Energy Modeling Forum 25)

CIMS hybrid energy-economy model: parameter estimation

CIMS micro-economic behavioral parameters

- Discrete choice surveys and probabilistic choice models to estimate market heterogeneity (v), technology-specific risks and preferences (i), and low-risk time preference (r).

Financial and intangible cost dynamics

- Technology learning from literature and neighbor effect from discrete choice surveys and literature.

CIMS macro-economic goods and services demand response

- Simple multiple regression of systems of energy service demand and product demand functions.
- Recent research into income effect and rebound effect of demand for energy services and energy-using devices.

Example of empirical research – the effect of greater energy efficiency on energy use?

direct rebound effect relates to individual services and may be small in many cases but large in some (air mobility)

evidence suggests 5-20%

productivity rebound effect: more generally, gains in energy productivity drive economic growth, spill-over to other energy services and foster the creation of new services (fridge => desk-top fridge, wine cooler, beer cooler, water cooler)

evidence uncertain, but could be extremely large

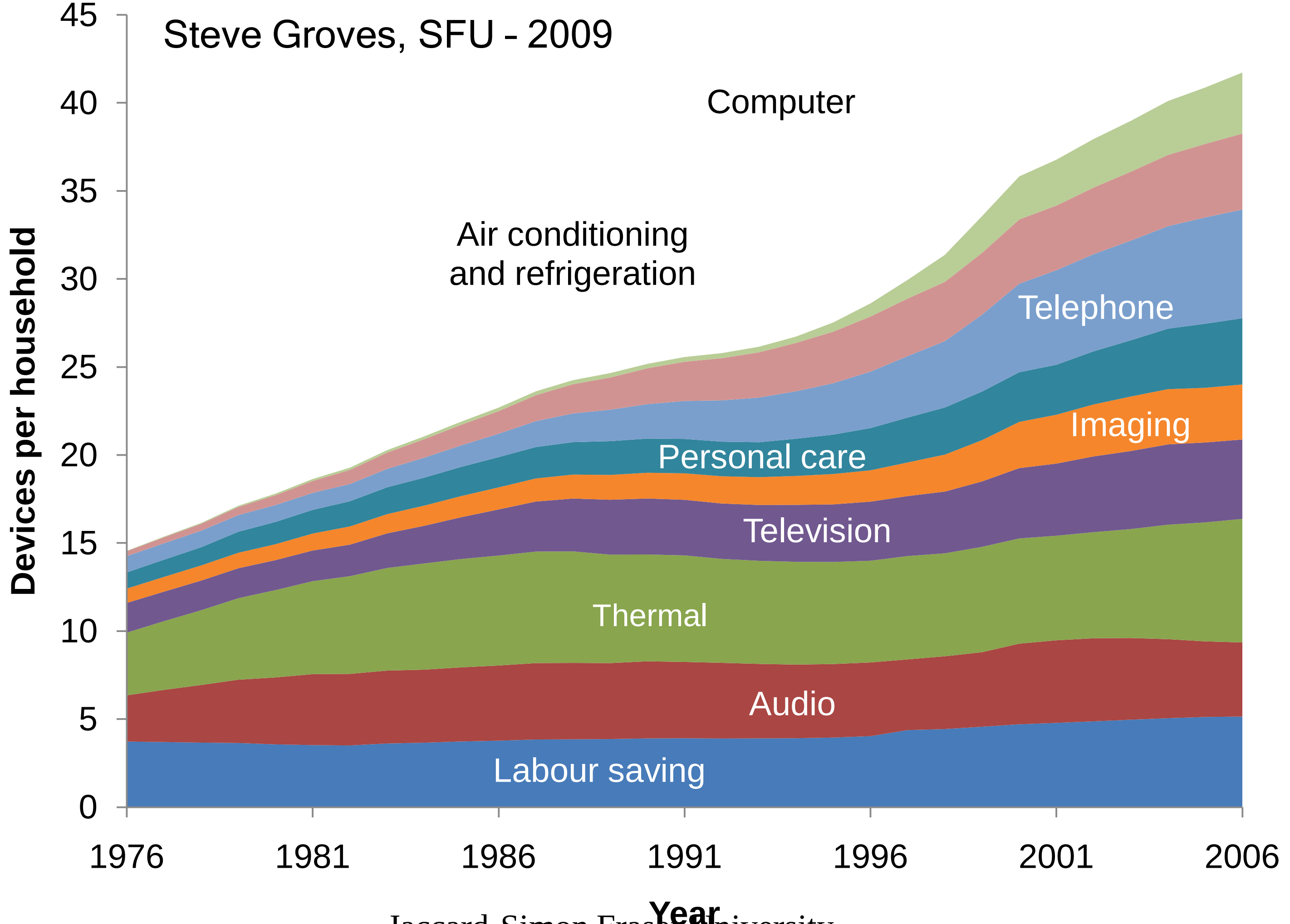
Service cost and service demand: UK lighting (1800 – 2000)

Energy service demand = f (GDP, service cost, other?)

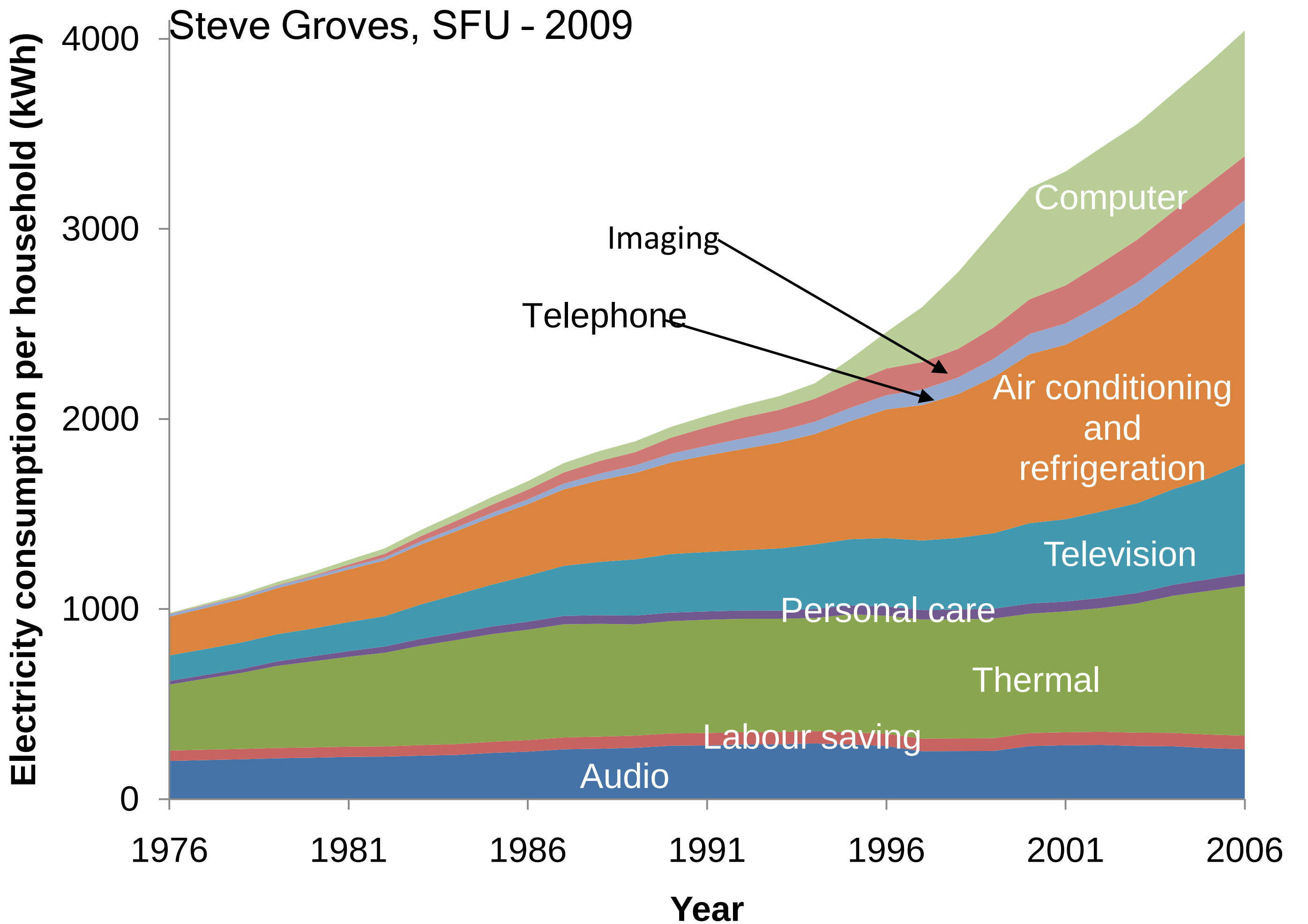
Year	1800	2000
GDP	A	A x 15
Lighting service cost	B	B x 1/3,000
Per capita consumption	C	C x 6,500

Source: Fouquet and Pearson, The Energy Journal, 2006

US data for "other" household devices - number



US data for "other" household services-devices: income or price effect?



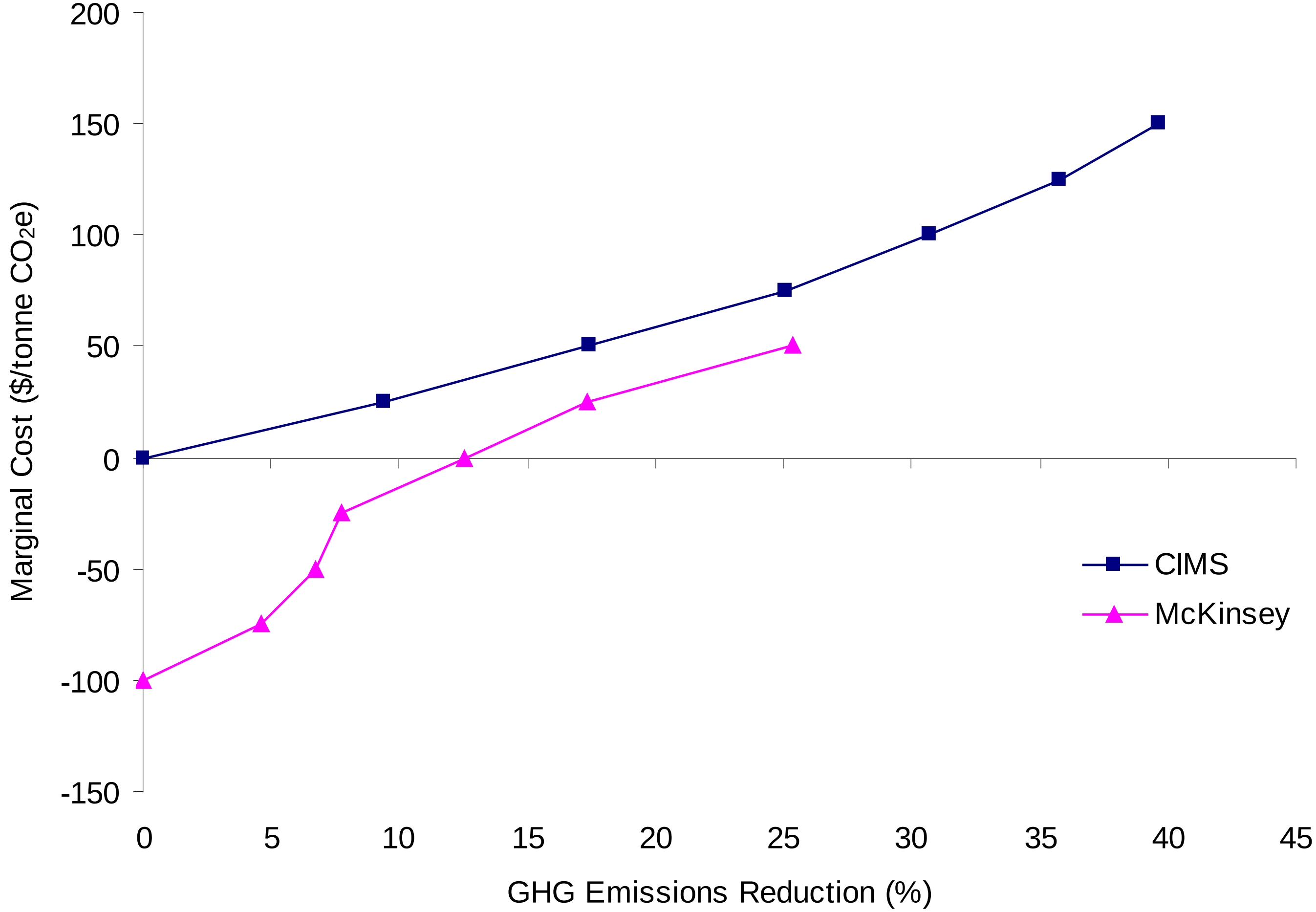
Comparing CIMS and McKinsey methods (from EMF 25)

	CIMS	McKinsey
Model Type	Hybrid.	Conventional bottom-up.
Tech Explicit?	Yes.	Yes.
Financial Costs?	Yes.	Yes.
Discount Rate	Node specific using RP & SP.	7%
Preference Costs?	Yes. Using RP & SP.	No.

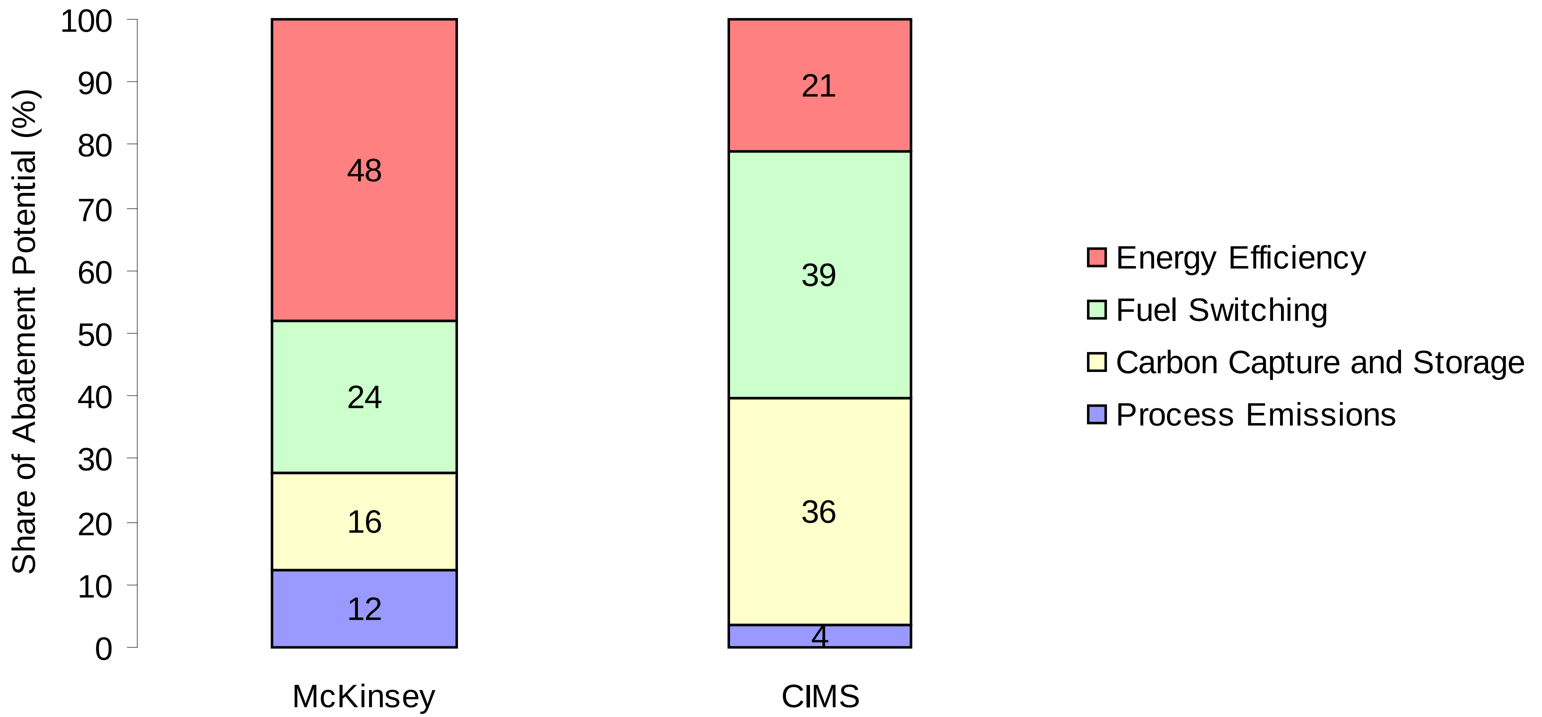
Comparing CIMS and McKinsey – continued

	CIMS	McKinsey
Market Heterogeneity?	Yes. Endogenous.	No or exogenous.
Integrated?	Yes. Actions interdependent.	No. Exogenous approximation.
Feedback Effects?	Yes. Energy S-D and macro.	No or exogenous.
Policy Simulation?	Yes (e.g. emissions price).	No.

CIMS and McKinsey GHG abatement cost curves: US in 2030



Contributions to GHG abatement at $50/tonne CO_2e: US in 2030



Changing CIMS assumptions

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Financial Costs?	Yes.	Yes.
Discount Rate	~~Node specific using RP & SP.~~ **7%**	7%
Preference Costs?	~~Yes. Using RP & SP.~~ **No.**	No.

Changing CIMS assumptions - continued

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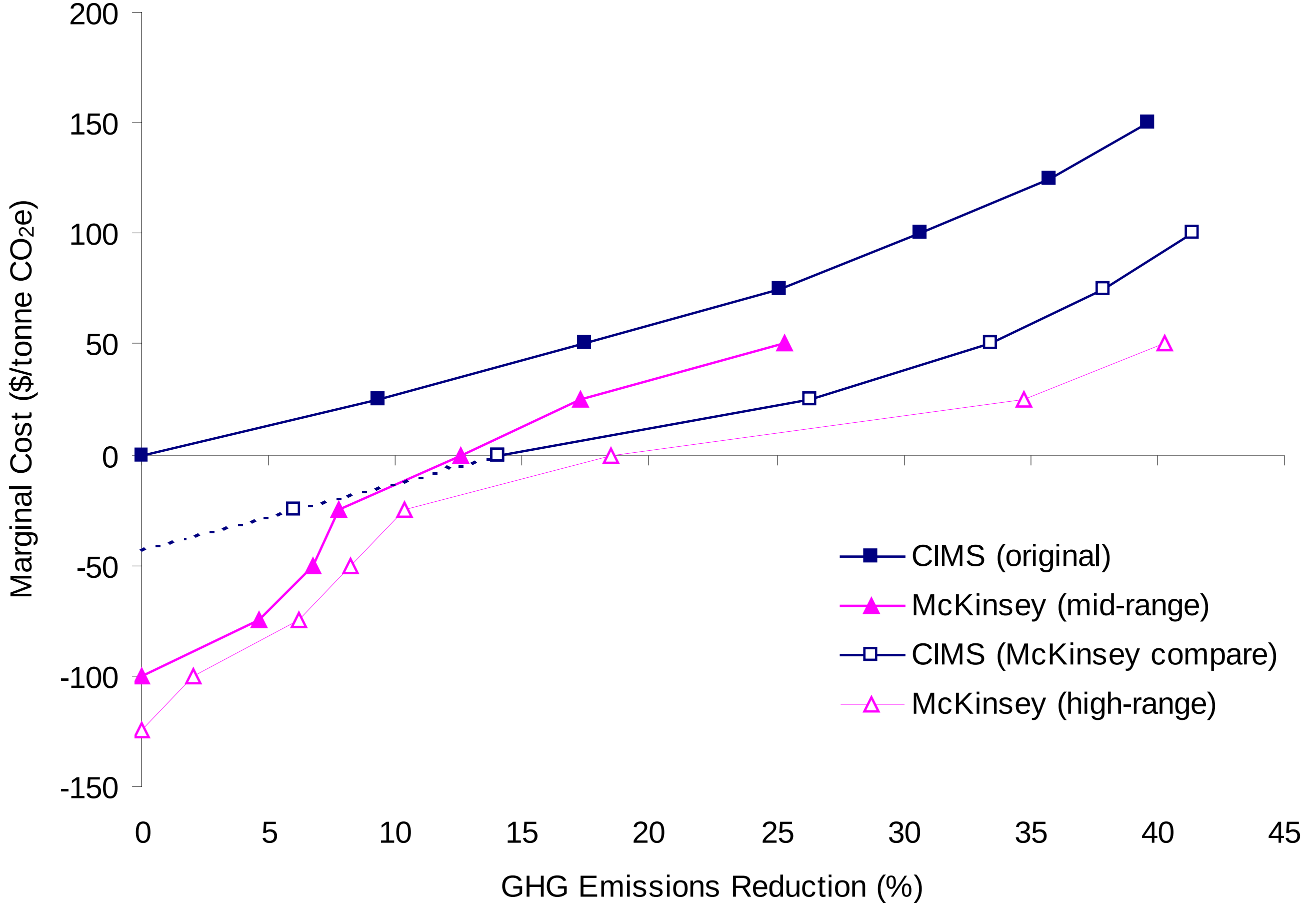
Market Heterogeneity?	Yes. Endogenous.	No or exogenous.
Integrated?	Yes. Actions interdependent.	No. Exogenous approximation.
Feedback Effects?	~~Yes. Energy S-D and macro.~~ **Partly disabled.**	No or exogenous.

GHG abatement cost curves: US 2030



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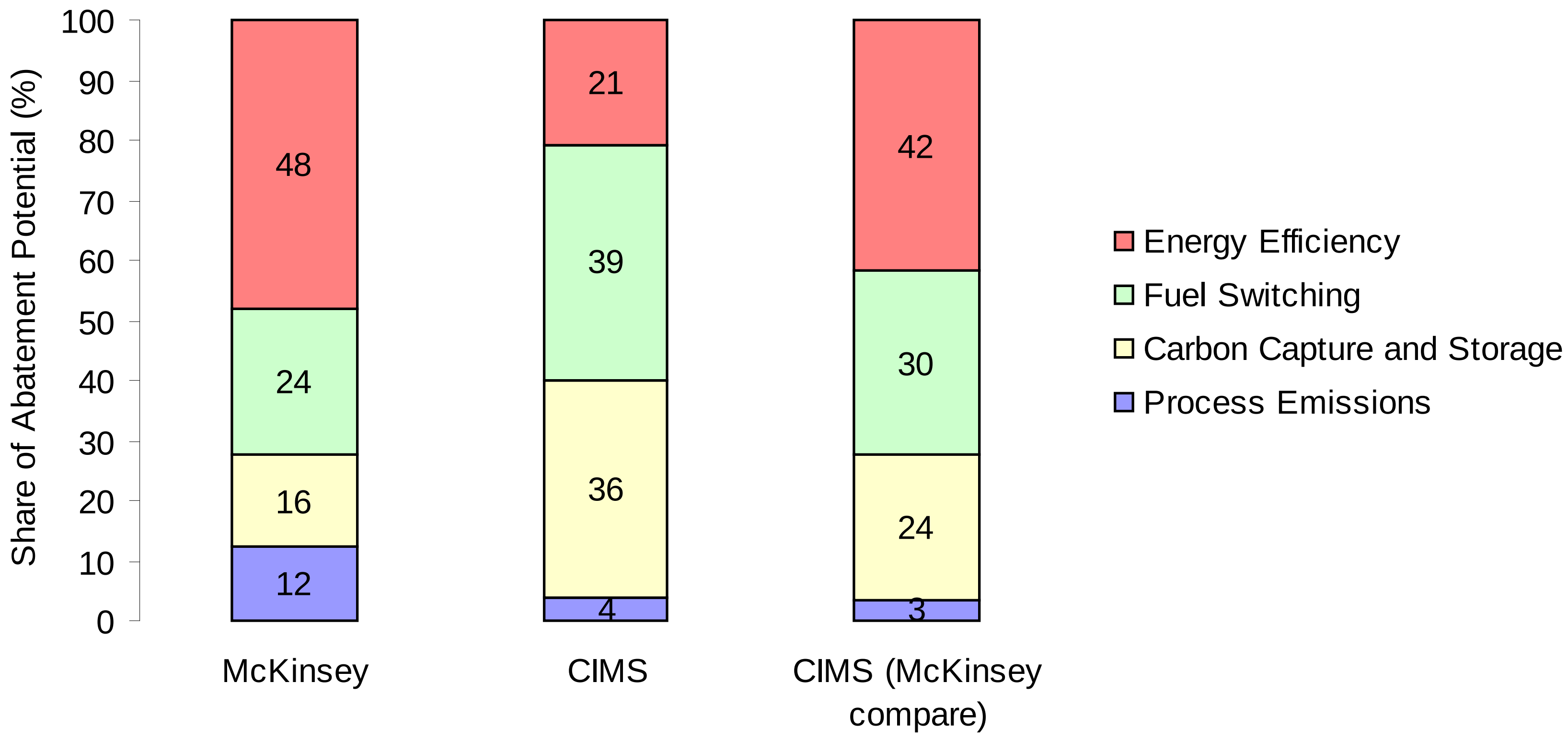


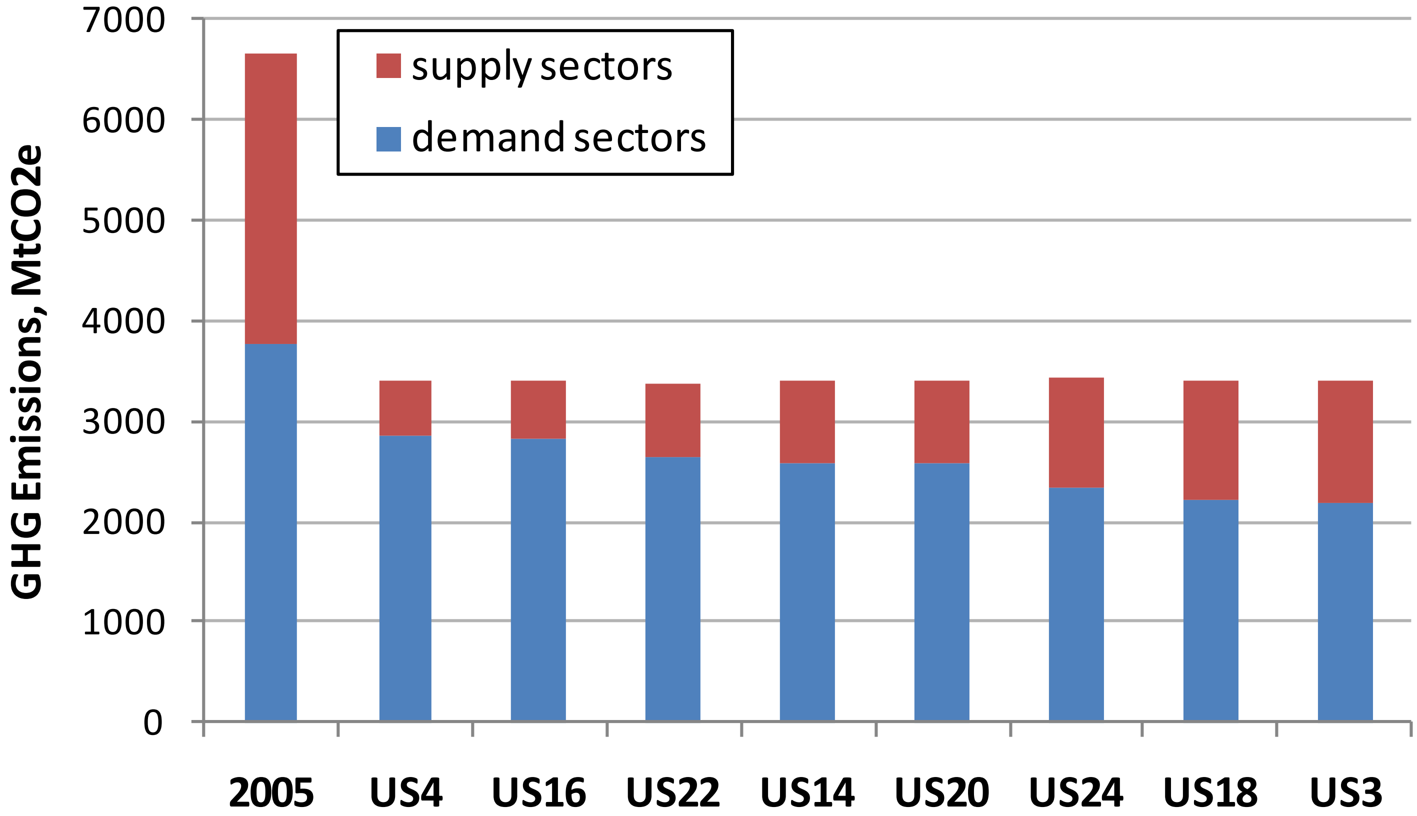
III. An energy-economy model to estimate efficiency and other abatement options under alternative targets and policies (from Energy Modeling Forum 24)

EMF 24 Study Parameters

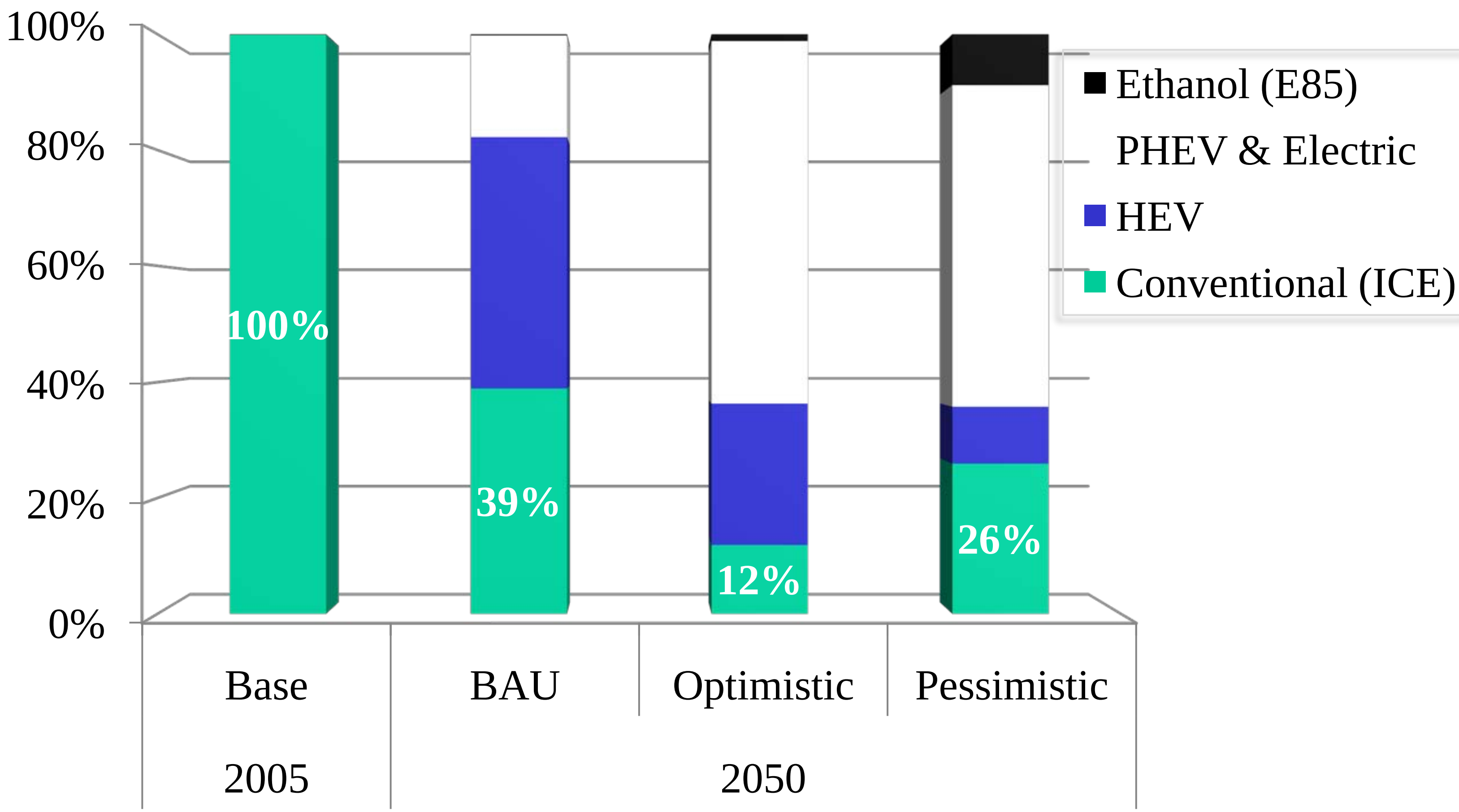
- **Technology Assumptions:** optimistic/pessimistic
  - End-use
  - CCS
  - Nuclear
  - Wind & Solar
  - Bioenergy

- **Policy** :
  - 50% Cap below 2005 levels

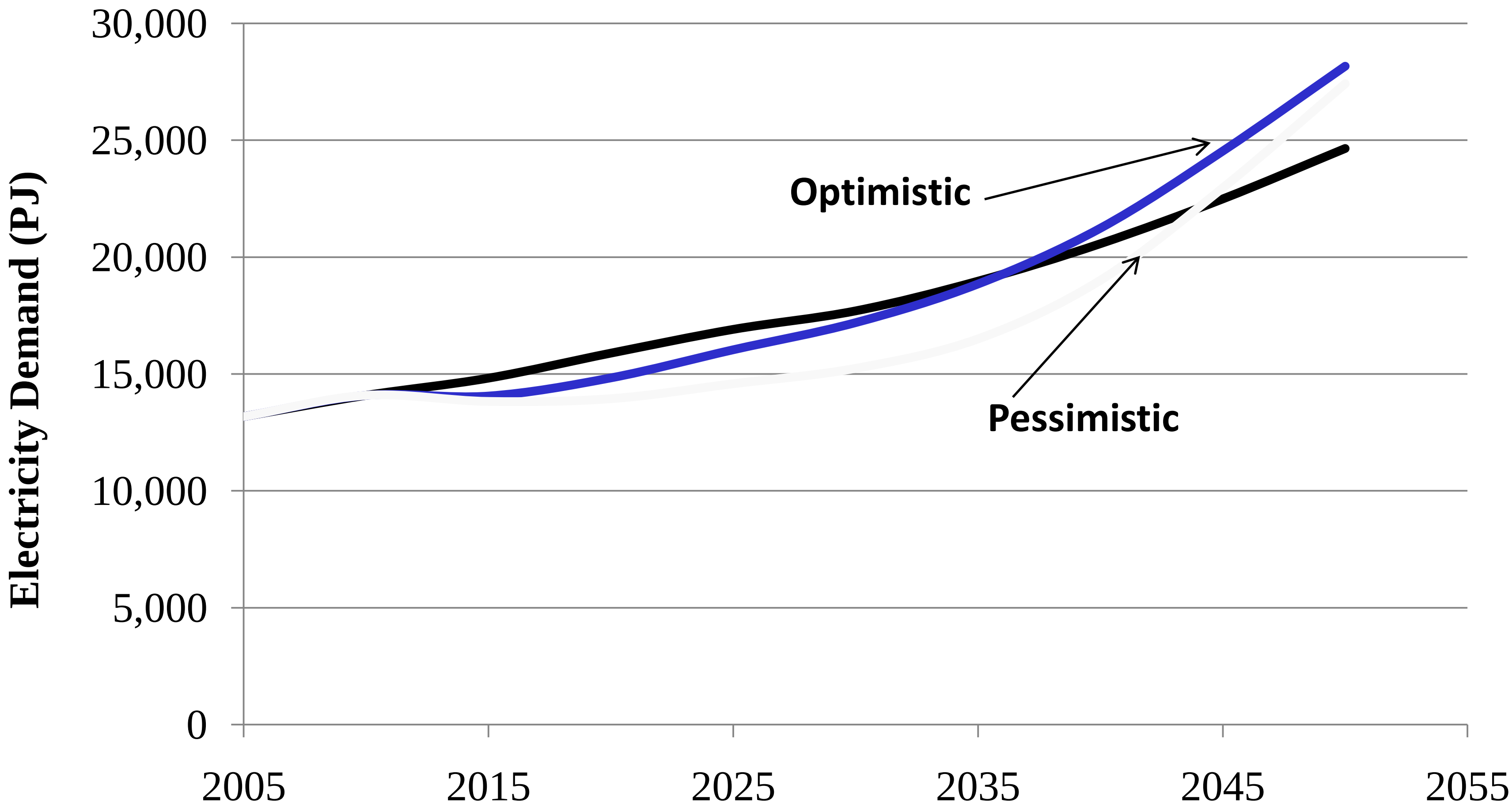
Achieving 50% GHG reduction by 2050 requires vast reduction from supply-side – in all scenarios



Achieving 50% by 2050 requires big change in vehicle stocks



Achieving 50% causes increased electricity use which offsets increased end-use efficiency



Conclusion

Using a hybrid model, we find higher costs for energy efficiency and thus also for GHG abatement than McKinsey-type bottom-up analysis.

The main reason is that hybrid models incorporate parameters reflecting technology-specific risk and quality of service into their estimates of technology costs.

When analysis includes productivity rebound effects that offset in part efficiency gains, then fuel switching and perhaps carbon capture must play a large role in GHG abatement.

Our policies should reflect this now. Energy efficiency policies must be accompanied by GHG pricing and/or regulations affecting technology or fuel choices.

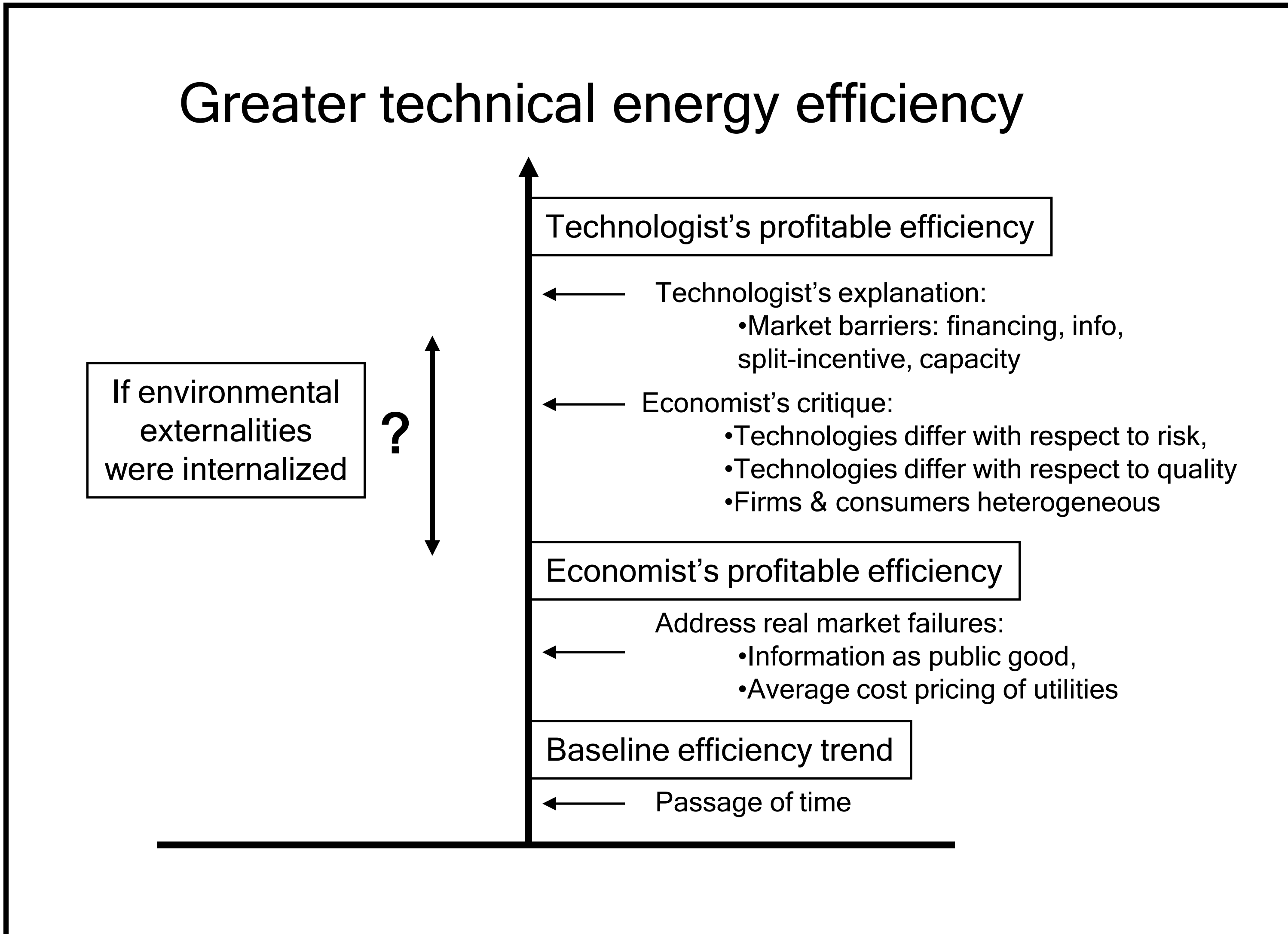
Conclusion continued

As an economist, I should be explaining how emissions pricing saves money relative to sector-specific, technology-specific, and fuel-specific GHG emissions regulations.

However, when the needed reduction is 50% by mid-century (80% if scientists are correct and our politicians sincere) it may not matter if we rely mostly on regulations. Emissions must fall dramatically from supply-side and demand-side.

If, instead, we insist on emissions pricing, and never achieve this because of political constraints, then our approach will help ensure a horrendous environmental outcome – with huge costs for all.

Extra slides


Greater technical energy efficiency
Technologist's profitable efficiency
Technologist's explanation:
•Market barriers: financing, info, split-incentive, capacity
Economist's critique:
•Technologies differ with respect to risk,
•Technologies differ with respect to quality
•Firms & consumers heterogeneous
If environmental externalities were internalized
?
Economist's profitable efficiency
Address real market failures:
•Information as public good,
•Average cost pricing of utilities
Baseline efficiency trend
Passage of time

Technology and preference dynamics: CIMS

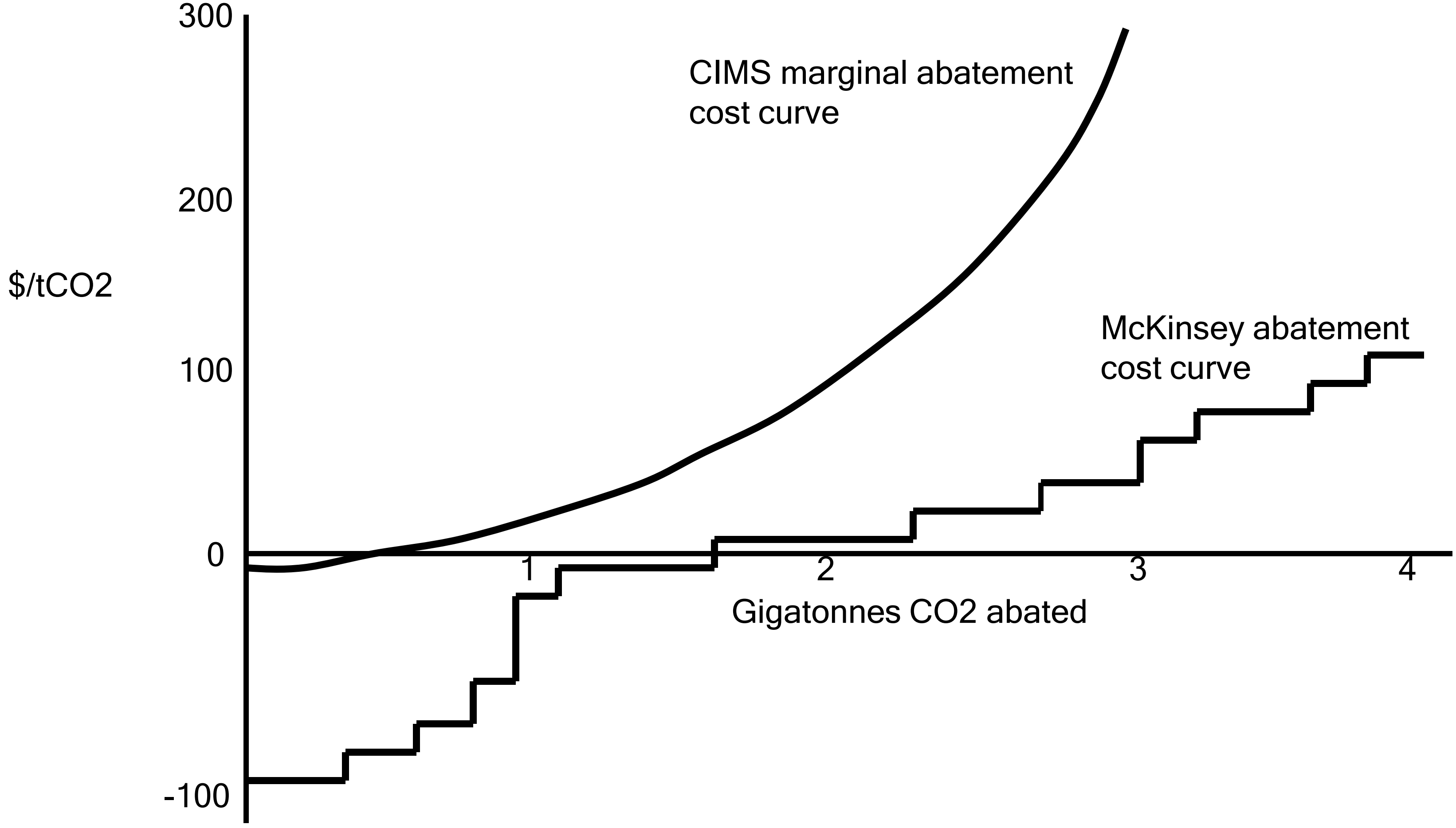
Declining capital cost function

- 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

Declining intangible cost function

- Links the intangible costs of a technology in a given period with its market share in the previous period
- Reflects improved availability of information and decreased perceptions of risk – the "neighbor effect"
- Mostly estimated from our own empirical studies

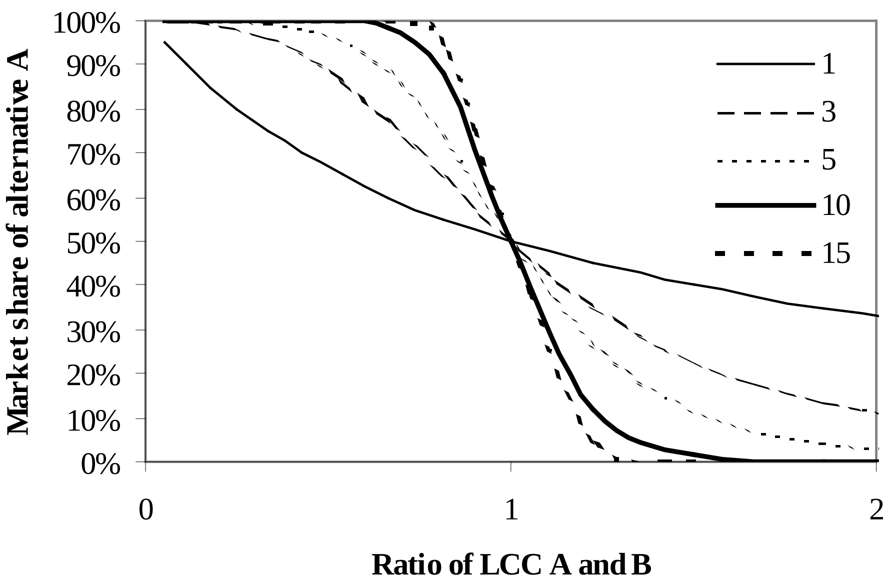
McKinsey vs. CIMS EMF 25 (US – 2030)



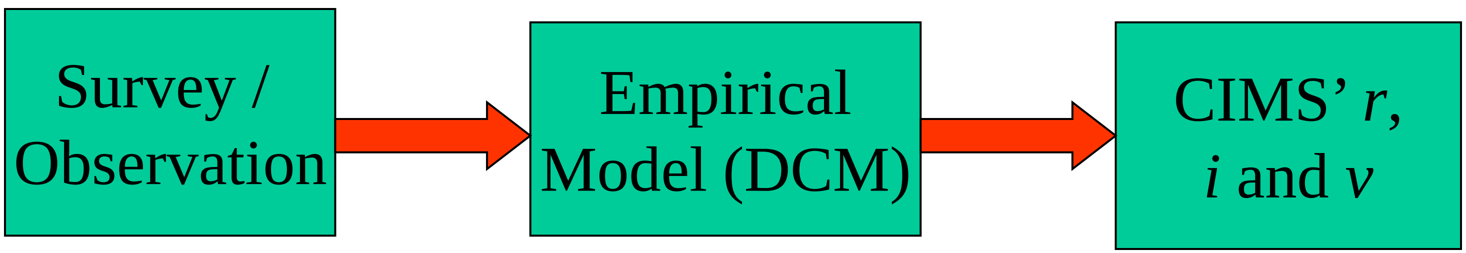
CIMS – technology share algorithm for new stocks

$$MS_j = \frac{\left[CC_j * \frac{r}{1-(1+r)^{-n}} + OC_j + EC_j + i_j\right]^{-v}}{\sum_{k=1}^{K}\left\{\left[CC_k * \frac{r}{1-(1+r)^{-n}} + OC_k + EC_k + i_k\right]^{-v}\right\}}$$

- **Discount rate (r)** - *time preference, option value, risk premium*
- **Intangible cost (i)** - *costs and benefits additional to simple financial costs*
- **Market heterogeneity (v)** - *different consumers and businesses have different preferences and perceptions, and may experience different costs in different locations.*



Discrete choice models to estimate r, i and v in CIMS



Standard discrete choice model for technology choice surveys

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

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

$v =$ ordinary least squares to estimate value for which predictions from CIMS are consistent with those from the DCM model. Depends on size of error terms relative to values of beta parameters.

CIMS technology learning and neighbor effect functions

–capital stock turnover and technology-specific progress ratios for capital cost or life cycle cost CC = *f*(cumulative production)

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

–technology-specific intangible cost function related to market share as in product market forecasting – key technological areas

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

EMF 25: simulating US energy and GHG policies