

Confronting the Challenge of Hybrid Modeling: Using Discrete Choice Models to Inform the Behavioural Parameters of a Hybrid Model

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ABSTRACT

The development of hybrid models represents an important step in energy economy modeling, as hybrid models embody the most useful features of both top-down and bottom-up models. Hybrid models explicitly represent technologies in a similar way to bottom-up models, thus enabling policy makers to understand the effects of technology-specific policies on energy consumption and the economy. However, to simulate consumer choice between alternative technologies and processes, hybrid models diverge from bottom-up models to use the behaviourally realistic approach of top-down models, resulting in a simulation model rather than an optimization model, which is ultimately of more use to policy makers.

The primary challenge in developing a representative hybrid model lies in specifying the algorithm to simulate consumer choice between alternative technologies. The algorithm needs to capture the fundamentals of consumer behaviour at a disaggregate level. This essentially involves estimating the empirically derived aggregate parameters used in top-down modeling at a technology specific level.

Discrete choice models (DCMs) are well suited to provide this information. DCMs use empirical data from historical or hypothetical technology choices by consumers to determine the relative importance of technology attributes to adoption of that technology. However, where DCMs have been used for predicting consumer behaviour relating to energy use decisions, the models have been run independent of a whole economy model, meaning that important system feedbacks have been ignored. By using empirically derived DCMs to inform the behavioural parameters of a hybrid model, the behavioural realism of the DCM can be coupled with the system feedbacks of the energy economy hybrid model to produce an integrated model that is both behaviourally realistic and technologically explicit.

Introduction

Policy making in the energy sector is strongly influenced by models designed to forecast the effects of policies on energy demand, economic output, and environmental pollution. Heavy use of such models has spurred the creation of many different energy models throughout the past quarter-century. These can generally be described as top-down models, which describe the energy system in terms of aggregate relationships formulated empirically from historical data, or bottom-up models, which determine the financially cheapest way to achieve a given target based on the best available technologies and processes.

Both types of models are being used to predict the potential economic effects of climate change policy. Because of their different structures, the two types of models tend to predict very different economic outcomes even when based on similar assumptions. Top-down models tend to predict high costs of compliance with new policies (e.g. climate policy)

while bottom-up models tend to predict low costs¹. This wide spread in modeling results is confusing to policy makers, and although interesting academically, ultimately decreases the practical value of such models in real-world policy analysis².

As we move into an era where energy policy could be poised for dramatic changes in response to environmental pressures, reliable energy-economy models will be ever more important. The divergent estimates and theoretical weaknesses of traditional top-down and bottom-up models in predicting outcomes of policies point towards the need for a new generation of energy-economy models.

Several attempts over the past twenty years have been made to reconcile the strengths of top-down and bottom-up energy economy models into a hybrid form of energy economy model. Hybrid models incorporate some form of technological explicitness (from bottom-up models) with some form of behavioural realism and macroeconomic feedbacks (from top-down models) into an integrated energy economy model. The objective of this paper is to briefly review efforts at hybrid modeling and discuss a new form of hybrid model that accounts for the concerns of both the top-down and bottom-up camps.

The paper begins by reviewing the relevant developments of energy-economy models, with a focus on the top-down/bottom-up controversy, in section 2. In section 3, we introduce the concept of hybrid modeling and describe several such models. Sections 4 and 5 are a discussion of how random utility models of discrete consumer choices can be used to augment the strength of hybrid models. Section 6 is a conclusion.

Development of Energy-Economy Models

Energy economy models can be characterized by the degree to which they embody three important qualities – technological explicitness, behavioural realism, and incorporation of macroeconomic feedbacks (IPCC 1996, pp. 283-285; Jaccard et al 2003, pp. 56-58).

Technologically explicit models contain a database of technologies (or proxies for technologies) to fill various service demands. Technologies are characterized by capital and operating costs, fuel consumption, service outputs, and emissions. Energy use is calculated by summing the fuel consumption for each of the various end-uses of energy in the economy based on the type of technologies in use. The primary advantage of technological explicitness is that policies designed to influence the diffusion of technologies (one of the primary tools of policy makers) can be explicitly modeled. Another advantage is that it is possible to explore the market penetration and resulting effects of yet-to-be-commercialized technologies.

Behaviourally realistic models are models empirically based on observations about the relationship between energy use or technology choice and energy price, technology price, income or GDP, and/or other variables. The alternative to behavioural realism is a model based on theory, such as the ‘rational economic man’ (cost-minimization) model. The term ‘behavioural realism’ is relative, since any model is obviously incapable of fully accounting for the interplay of measurable and non-measurable variables that influence any decision. In

¹ These trends in cost outcomes do not necessarily follow from model structure (e.g. one can imagine developing a top-down model with parameters that would predict cheap policy compliance costs), but historically top-down models have predicted high policy compliance costs and vice-versa.

² Model structure is only one of many factors that produce divergent results in different models. Different definitions of costs and benefits also lead to a spread in modeling results.

fact, analysts have demonstrated that many so-called behaviourally realistic models have produced inaccurate predictions in the past (Shylakhter et al 1994; Craig et al 2002). However, we still refer to models based on empirical data as behaviourally realistic because they capture better the behaviour of consumers than theory-based alternatives.

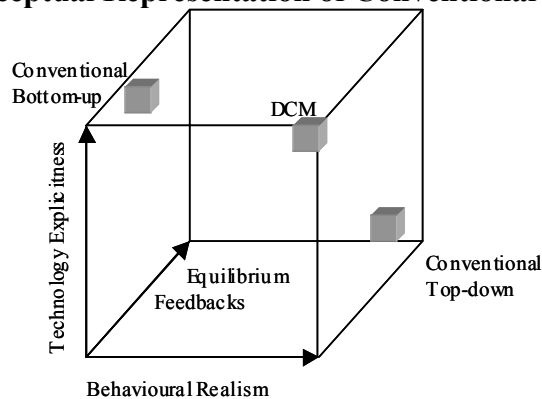
Models that incorporate macroeconomic feedbacks attempt to determine the equilibrium effects of a given policy. This is accomplished by: (1) ensuring equilibrium within the energy supply sector; i.e. allowing for complete adjustments to supply, demand, and prices within the energy sector following the introduction of a disturbance (policy); and (2) ensuring equilibrium feedback between the energy sector and other sectors; i.e. allowing for adjustments to commodity prices, demand, and supply as well as adjustments to investments, employment, and trade following the introduction of a disturbance. Models that only account for (1) are termed partial equilibrium models, while models that account for (1) and (2) are termed general equilibrium models. Using general equilibrium models is particularly important when disturbances to the energy sector are large enough to cause significant macroeconomic effects.

The possession of each of these three characteristics is an asset to models designed to predict the economic and environmental effects of energy policies. Unfortunately, very few of the energy models that have been developed over the past quarter-century are strong in all three categories. The two main categories of energy economy models, bottom-up and top-down, actually represent virtual mirror images of one another with respect to these categories; where one is strong, the other is weak (IPCC 1996, p. 284).

Top-down models use historical market data to derive aggregate relationships between energy and commodity price and market shares in various sectors of the economy. These sectors are then interacted in an equilibrium framework to determine total economic output and energy and commodity inputs. Because they are based on empirical data about aggregate market behaviour, top-down models are considered behaviourally realistic. Top-down models also incorporate macroeconomic effects by nature; they are general equilibrium models. However, top-down models are not able to explicitly model the evolution of technology or policies designed to affect the diffusion of individual technologies.

In contrast, bottom-up models are technologically explicit. They are essentially a database of technologies that can be used to fill the various service demands in the economy. To determine which technologies are used in different policy scenarios, bottom-up models require an algorithm to choose between technologies. For this, they generally rely on the criteria of least cost in which the technology that has the lowest life cycle cost, at the social discount rate, is chosen to fill 100% of the new demand in each service niche. In this respect, bottom-up models are not behaviourally realistic, since they use theory rather than real data to simulate the evolution of technology. Bottom-up models are also traditionally weak in modeling macroeconomic effects of policies, usually limiting their scope to partial equilibrium within the energy sector. Figure 1 is a conceptual representation of the different strengths of top-down and bottom-up models in the three dimensions discussed.

Figure 1. Conceptual Representation of Conventional Energy Models



The structures of both top-down and bottom-up models contribute to certain inherent biases with their forecasts. Top-down models tend to systematically overestimate the economic costs of environmental energy policies for two main reasons. First, implicit in the top-down equilibrium framework is the assumption that the general equilibrium solution to the model is unique and represents the Pareto optimal allocation of resources (Laitner et al 2001, pp. 7-9). By definition then, any divergence from this equilibrium (e.g. policy) necessarily imposes costs on the economy. Second, top-down models are based in large part on two difficult-to-estimate parameters for which minor changes can have large effects on model outcome. The autonomous energy efficiency improvement (AEEI) represents the degree to which the energy efficiency of the economy will improve each year autonomously (i.e. in addition to those improvements that are the results of price changes). The elasticity of substitution (ESUB) represents the degree to which one aggregate input (e.g. capital, labour, energy) is substitutable for another. Both of these are crudely estimated from historical market behaviour and are generally treated as static in top-down models. This is problematic when the models are used to probe scenarios of the future which diverge widely from the past because changes in economic and environmental conditions influence consumer behaviour (Norton et al 1998), which in turn influences AEEI and ESUB. Treating these parameters as static amounts to the assumption that a changing environment influences neither behaviour nor technological evolution. This is particularly problematic because the magnitude of our current environmental goals (e.g. stabilizing concentrations of CO₂ in the atmosphere) requires non-marginal changes in behaviour and technology at rates never previously experienced except in times of economic or resource crisis (Azar and Dowlatabadi 1999).

Bottom-up models tend to systematically underestimate the economic costs of environmental energy policies. Since they do not account for consumer preferences, they overestimate the willingness of the market to switch to cleaner technologies, which often have a lower financial life-cycle cost than polluting technologies at the social discount rate, but which can have a higher welfare cost due to risks, option value, and intangibles.

Grubb et al documented this disparity between bottom-up and top-down forecasts in a survey of 20 energy economy models predicting the GDP effects of climate change mitigation policies in the US (1993). They found the bottom-up models surveyed predicted low or negative costs for climate change mitigation, while top-down models predicted much higher costs on average.

Evidence of this disparity and the debate between top-down and bottom-up camps prompted modellers to attempt to reconcile some of the differences between the two

competing structures (IPCC 1996, pp. 287-289). Top-down models have evolved to increase the degree to which they are able to represent technologies by disaggregating demand functions. Current bottom-up models often include macroeconomic feedbacks in their forecasts and are making the first steps at increasing the degree to which they depict consumer behaviour by using empirical discount rates rather than the social discount rate in predicting technology choices.

Some modellers, recognizing the fundamental problems inherent in either one approach, have turned to a new generation of models that attempts to borrow from the strengths of both top-down and bottom-up models. These new models, called hybrid models, could prove useful to policy makers assessing the relative strengths of climate change mitigation and other policies.

Hybrid Models

We define a hybrid model as an energy economy model that attempts to bridge the methodological schism between bottom-up and top-down modeling by incorporating behavioural realism and technological explicitness in a model that also accounts for macroeconomic feedbacks (Jaccard et al 2003). Several attempts have been made at this type of hybrid modeling.

Hoffman and Jorgenson (1977) developed the earliest documented hybrid model. Their model is based on an input-output model of the US industrial and private sectors, which feeds energy price and energy and commodity demand values to a bottom-up linear programming model. The bottom-up model then determines the cheapest way of meeting the required constraints by choosing the 'optimal' technologies. The bottom-up model generates an updated price estimate for energy and other commodities, and these are fed back into the top-down model to adjust demand numbers. This process iterates until convergence.

Hoffman and Jorgenson's model represents a conceptual improvement over both traditional top-down and bottom-up models. Compared to bottom-up models, Hoffman and Jorgenson's model incorporates macroeconomic feedbacks as well as some behavioural realism because it includes relationships for demand effects and substitution in sectors other than the energy sector. However, since the energy sector (bottom-up) model is a linear programming (financial cost optimization) model, Hoffman and Jorgenson's model is not behaviourally realistic (consumers are not cost-minimizers).

More recently, Jacobsen (1998) has developed a hybrid model for the Danish economy. His model, Hybris, links the Danish macroeconomic model, ADAM, with three bottom-up modules representing energy supply, household electricity demand, and household heat demand. The top-down model determines demand for energy in each sub-module. The sub-modules use a cost-minimization algorithm to determine fuel use in each module. The evolution of technology stocks, however, is simulated using the top-down model, while only fuel demand is determined in the bottom-up model. This limits the effectiveness of the bottom-up model. In essence, Hybris is similar to a traditional top-down model, with more technological explicitness in the short-term only. In the long-term (for capital stock turnover) it is not significantly different than a traditional top-down model.

Koopmans and Willem te Velde (2001) use NEMO, a top-down model of the Netherlands economy whose parameters are estimated from runs of ICARUS, a bottom-up model, to predict changes in energy demand. ICARUS is a vintage model that calculates the

economic and technical potential for energy efficiency improvements in the Netherlands. Recognizing that economic potential does not represent actual consumer behaviour, Koopmans and Willem te Velde changed the discount rate in their model until energy efficiency improvements predicted by the model were more realistic. While their model remains a financial cost optimization model, the attempt to improve behavioural realism of the bottom-up part of their integrated model is an important step.

Bohringer (1998) estimates changes in input (labour, energy) demand at different tax rates in the electricity production sector using both a computable general equilibrium (CGE) model and an activity analysis (bottom-up) model of the sector. While he finds that both models predict similar reductions in energy consumption at varying tax rates, the results diverge significantly in predicting sector effects (labour demand). Bohringer thus suggests that using activity analysis in a CGE model could be useful.

All of these efforts at hybrid modeling were initiated because the authors recognized the inherent weaknesses of using a top-down or bottom-up approach in isolation. All of the models described, however, focus uniquely on the problem of integrating technological explicitness with macroeconomic feedbacks. While they appear to succeed on this front, none of the models described thus far is a true hybrid model because each fails to sufficiently incorporate behavioural realism in the bottom-up model (or module). In each case, a bottom-up financial cost optimization model is linked to a top-down model to arrive at a hybrid model. The top-down model is assumed to account for the behavioural relationships, implying that the bottom-up model does not need to. However, by not accounting for behavioural relationships in the bottom-up model, the top-down model receives overly optimistic estimates of costs based on unrealistic assumptions of consumer behaviour from the bottom-up model. A similar critique could therefore be levelled at these models as at traditional bottom-up models. In order to develop a hybrid model that is both technologically explicit and behaviourally realistic, it is imperative that behavioural realism is embedded directly into the bottom-up component.

The CIMS model of the Canadian energy-economy attempts to do this (Jaccard et al 2003; Nyboer 1997). CIMS is a technology vintage model, meaning that it tracks the evolution of technology stocks over time through retirements, retrofits, and new purchases. CIMS calculates energy costs (and GHG production) at each service demand node in the economy (e.g. there is a node for heated commercial floor space, and one for person-kilometres-travelled) by simulating choices of energy-using technologies by consumers at each node. New market shares of competing technologies are simulated at each competition node based on their life cycle cost according to the following formula³:

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

³ CIMS also employs a number of hard controls to limit the penetration of technologies to certain levels (e.g. a maximum of one washing machine per household) as well as a declining capital cost function to simulate learning-by-doing and economies of scale exhibited particularly for new technologies.

Where MS_j = market share of technology j , CC = capital cost, MC = maintenance and operation cost, EC = energy cost, i = intangible cost (for example, there is an intangible cost associated with public transit due to inconvenience, lower status, etc), r = private discount rate, and v = measure of market heterogeneity. The main part of the formula (the part inside the square brackets) is, in essence, simply the levelized life cycle cost (LCC) of each technology. In this formulation, the inverse power function acts to distribute the penetration of that particular technology j relative to all other technologies k . A high value of v means that the technology with the lowest LCC captures almost the entire market share. A low value for v means that the market shares of new equipment are distributed fairly evenly, even if their LCCs differ fairly significantly.

The challenge in conducting high quality hybrid modeling is empirically estimating the technology-level behavioural parameters (v , i , and r). While a number of methods exist that could be conducive to this application, currently the most appropriate solution seems to be using discrete choice models (DCMs) to estimate the parameters.

Discrete Choice Models

Discrete choice models were developed in the 1970s to serve as tools for forecasting discrete (as opposed to continuous) choices, particularly in the fields of marketing, tourism, and transportation demand⁴. They are based on the postulate that consumers are utility-maximizers: when faced with a particular choice set, consumers choose the option that brings them the most satisfaction or utility⁵. In a further refinement of this theory, McFadden (1974) conjectured that a consumer views each option in the choice set as a bundle of attributes, and makes a choice by combining perceptions of the attributes using an implicit utility function.

The goal of the analyst attempting to forecast choices using discrete choice models is to estimate a consumer's (or a segment of society's) implicit utility function. This is done by observing many choices made by a consumer (or a larger group) and determining the importance of the various attributes of the choices in the choice set using non-linear regression. In general, the utility measured by the analyst is assumed to be a linear combination of the observed attributes of the technology multiplied by weighting coefficients estimated in the regression:

$$V_j = \beta_j + \sum_{k=1}^K \beta_k x_{jk} \quad (2)$$

Where the β_k 's are the set of K weighting coefficients estimated from the data, the x_{jk} 's are set of K attributes of technology j , and β_j is an alternative specific constant that captures attributes of the technology not measured explicitly but that vary systematically with j . For example, a possible function for the observed utility of car j is:

$$V_j = \beta_j + \beta_1(CC_j) + \beta_2(OC_j) + \beta_3(TT_j) \quad (3)$$

⁴ For a more complete overview of DCMs, see for example, Ben-Akiva and Lerman (1985), Louviere et al (2000), or Train (2002).

⁵ Although there is a debate in economics and psychology about the appropriate heuristic for understanding consumer choices, utility maximization is generally thought to provide reasonable estimates of the *outcome* of consumer decision-making process, even if it isn't appropriate for actually understanding the *process*.

Where CC is the capital cost of car j , OC is the operating cost, and TT is the travel time. Due to contextual and temporal variation and other non-measurable factors in consumer choices however, the utilities are not fully measurable to the analyst. The utility of each function is therefore a random variable, anchored at the utility measured by the analyst, but varying with a probability distribution given by an error term:

$$U_j = V_j + \varepsilon_j \quad (4)$$

Where U_j is the total utility (random variable), V_j is the measurable utility, and ε_j is the non-measurable (random) utility, or error term. Since the total utility of each alternative is a random variable, the analyst can only forecast the probability that a consumer will choose option j from the choice set A at any moment as:

$$\Pr(j | A) = \Pr(U_j > U_i) \forall i \in A, j \neq i \quad (5)$$

Substituting for U_i and U_j gives:

$$\Pr(j | A) = \Pr(V_j - V_i > \varepsilon_i - \varepsilon_j) \quad (6)$$

Eq. (6) can only be solved if an error distribution is assumed for ε_i and ε_j . For analytical tractability, it is usually assumed that ε_i and ε_j follow Type I Extreme Value distributions⁶. Under this assumption, integration of Eq. (6) gives the multinomial logit function:

$$\Pr(j | A) = \frac{e^{V_j}}{\sum_{j=1}^J e^{V_j}} \quad (7)$$

This representation of discrete technology choice is consistent with the way that most energy using technologies are actually chosen (e.g. choice between buying an electric furnace versus a natural gas furnace is a discrete, not continuous, choice). Discrete choice modeling provides an analytical framework for quantifying the importance of various attributes of technologies, and predicting how consumers will respond to changes in those attributes. DeCanio and Laitner (1997) note that DCMs can provide biased estimates of economic parameters (e.g. discount rate) if they are based on snapshots of the economy at one instant in a technology's diffusion process. They suggest integrating DCMs with technology diffusion data to correct this problem. While we believe that the explanatory power of DCMs could be much enhanced by using time-series data in this manner, we are also of the opinion that 'static' DCMs can provide useful behavioural data to energy models.

Returning to our representation of energy models by their positions along the three axes of technological explicitness, behavioural realism, and macroeconomic feedback, we can characterize DCMs as in Figure 1. They are behaviourally realistic models at the single technology level with no equilibrium feedbacks.

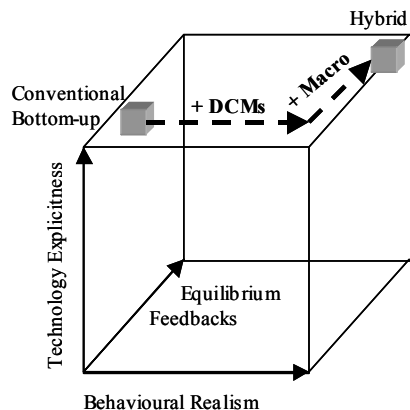
⁶ We have no reason to believe that the errors should actually be distributed according to this type of distribution, and recently, analysts have solved Eq. (6) for other types of distributions.

Integrating DCMs into Energy-Economy Models

While DCMs provide a workable means to predict technology choice on a single-technology level, they are of limited use to policy makers as stand-alone models since they are unable to account for the effects of feedbacks throughout the energy system. For example, using a DCM on its own to predict the effect of a subsidy on efficient appliances would be misleading since the choice being simulated depends critically on the price of electricity, which in turn depends on efficiency and fuel switching efforts in the electricity sector and any other programs or policies that change electricity demand and supply. The energy-saving effect and cost of the appliance efficiency program would therefore be unknown save through simulating the entire energy-economy system.

A solution is to capture the technology-specific behavioural realism of the DCM and make it useful to policy makers by embedding it in an integrated bottom-up model. By using a bottom-up model structure and replacing the traditional cost-minimization algorithm with a DCM at each technology decision node, a behaviourally realistic and technologically explicit model is obtained. This model can be combined with a top-down model using techniques discussed by Bohringer, Jacobsen, Jorgenson and Hoffman, and Koopmans and Willem te Velde to arrive at a true hybrid model that is behaviourally realistic, technologically explicit, and incorporates macroeconomic feedbacks. Figure 2 is a representation of this form of hybrid model on the three dimensions discussed earlier.

Figure 2. Conceptual Representation of Hybrid Models



Integrating DCMs into CIMS requires calculation of the v , i , and r parameters in the CIMS market share equation from the β parameters in the DCM market share equation. Train (1985) discusses estimation of the discount rate from a DCM. If it is assumed that technologies have long lives and no depreciation (these assumptions apply generally to industrial technologies, but not as well to some individual consumer choices) and that real energy price stays constant, then the discount rate is simply the ratio of the capital cost to annual cost coefficients in the DCM⁷. Using Equation 3 as an example, the consumer's implicit discount rate would be $r = \beta_1/\beta_2$. Since CIMS compares technologies based on levelized life cycle cost, a similar technique is used to calculate the intangible costs for each technology, so that the annual intangible cost for technology j is (based on Equation 3):

⁷ If the assumptions discussed cannot be made, a more complicated discount rate equation can be formulated.

$$i_j = \frac{\beta_3}{\beta_2} TT_j + \frac{\beta_j}{\beta_2} \quad (8)$$

With r and each i_j calculated, v is then chosen so that market share predictions from CIMS match market share predictions from the DCM.

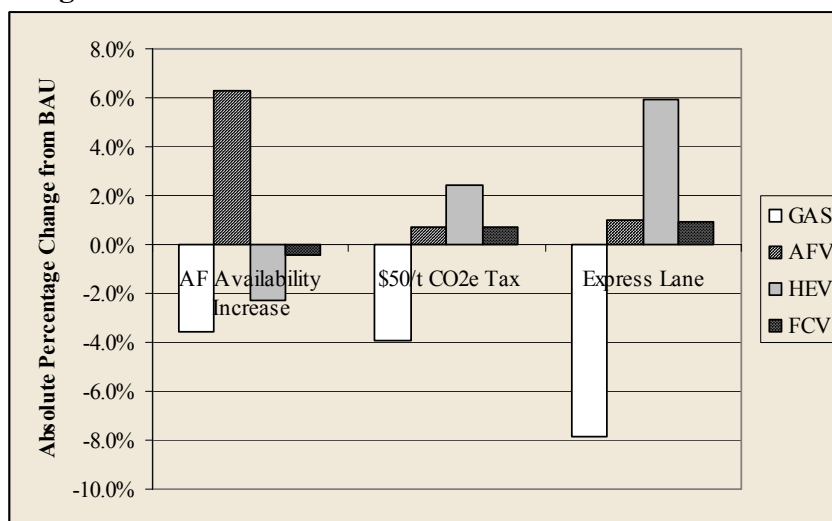
To illustrate the integration of DCMs into CIMS, Table 1 presents the results of three discrete choice surveys conducted during the past year by researchers at the Energy and Materials Research Group (EMRG) at Simon Fraser University to measure consumer behaviour in the residential, transportation, and industrial sectors of the Canadian economy. The DCMs have been transformed into CIMS parameters as discussed above.

Table 1. Results from Discrete Choice Models

Residential Space Heating Model		Transportation Vehicle Choice Model		Industrial Heat and Power Model	
Parameter	Value	Parameter	Value	Parameter	Value
Discount Rate (r)	9%	Discount Rate (r)	24%	Discount Rate (r)	34%
Heterogeneity (v)	2.3	Heterogeneity (v)	3.0	Heterogeneity (v)	1.4
Intangible Costs (i)		Intangible Costs (i)		Intangible Costs (i)	
Oil	0	Gasoline	1,800	Boiler	279,000
Electricity	308	Alternative Fuel	4,890	High Eff. Boiler	-241,000
Low Efficiency Gas	499	Hybrid	-1,090	Cogeneration	0
High Efficiency Gas	28	Fuel Cell	840		
Heat Pump	271				

Once the DCMs have been integrated into the energy economy model, the latter can be used to simulate the effects of both cost and non-cost policies. As an example, Figure 3 shows the new market share of vehicle types⁸ in Ontario in 2010 compared to business as usual (BAU) after the imposition of a \$50/tCO_{2e} tax, the increase in alternative fuel (propane, methanol, ethanol) availability from 25% of stations to 100% of stations, and the creation of highway express lanes available to all non-gasoline vehicles (including hybrid vehicles).

Figure 3. Market Share of New Vehicles in Ontario in 2010



⁸ GAS – gasoline; AFV – alternative fuel; HEV – hybrid electric; and FCV – fuel cell vehicle

Conclusions

While top-down and bottom-up models have been incrementally improving over the past quarter-century, they both face fundamental theoretical weaknesses that point towards a paradigm shift in energy-economy modeling. Hybrid models have arisen in the past twenty years to address this need, yet most hybrid models currently in existence are simple extensions of top-down and bottom-up models and do not fully remedy the problems with using the more traditional models. In particular, the failure of most hybrid models to include behavioural realism in the bottom-up model component is problematic because it makes the implicit yet erroneous assumption that consumers are financial cost minimizers.

Discrete choice models are a useful tool for addressing the challenge of capturing consumer preferences at a technology-specific level. By using discrete choice models in conjunction with an integrated bottom-up model, a model that is both technologically explicit and behaviourally realistic can be arrived at. Combining such a bottom-up model with a top-down macro-economic model would create a model strong in all modeling dimensions.

The development of hybrid models could help to reduce the spread of policy cost estimates in the literature that has confused policy makers and hampered progress in reaching environmental goals. Such hybrid models would be useful because they would allow for the detailed exploration of technological evolution and technology-centred policies while at the same time avoiding the unrealistic assumptions of previous generations of bottom-up models.

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