Combining Top-Down and Bottom-Up Approaches To Energy-Economy Modeling Using Discrete Choice Methods

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Recently, hybrid models of the energy-economy have been developed with the objective of combining the strengths of the traditional top-down and bottom-up approaches by simulating consumer and firm behavior at the technological level. We explore here the application of discrete choice research and modeling to the empirical estimation of key behavioral parameters representing technology choice in hybrid models. We estimate a discrete choice model of the industrial steam generation technology decision from a survey of 259 industrial firms in Canada. The results provide behavioral parameters for the CIMS energy-economy model. We then conduct a policy analysis and show the relative effects of an information program, technology subsidy, and carbon dioxide tax on the uptake of alternative industrial steam generation technologies, including boilers and cogeneration systems. We also show how empirically derived estimates of parameter uncertainty can be propagated through the model to provide uncertainty estimates for major model outputs.

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 energy-related pollution. This has spurred the creation of many different energy-economy models throughout the past quarter-century. These can generally be classified as top-down models, which describe the energy system in terms of aggregate relationships derived 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 used to predict the potential economic effects of energy-focused environmental policies, and, particularly in the past decade, climate change mitigation policies. Because of their different structures and definitions of costs, the two types of models tend to predict very different economic outcomes (Grubb et al., 1993; IPCC, 1996, Jaccard et al., 2003). Top-down models usually predict high costs of greenhouse gas emission reduction policies while bottom-up models usually predict low costs. This divergence in modeling results is confusing to policy makers, and although interesting academically, ultimately decreases the practical value of such models in real-world policy analysis. The structure and assumptions of both of the traditional types of models predispose them to these biases in cost predictions.

Bottom-up models determine the cost of emissions reduction by comparing the financial costs and emissions of different technologies using a social discount rate. They typically find that there are many cost-effective opportunities for emissions reduction, leading to what Jaffe and Stavins (1994) call an ‘energy efficiency gap’. However, this type of analysis ignores several important factors.

1. Consumers and firms face additional risks of adopting new technologies that are not captured by the social discount rate because their assets are less diversified than those of society as a whole (Sutherland, 1991).
2. Consumers and firms can derive ‘option value’ from waiting for more information before making a potentially risky and irreversible investment. This option value is not captured by the social discount rate (Dixit and Pindyck, 1994).
3. Consumers and firms are heterogeneous populations in terms of their preferences and the financial costs they face, so that even if a technology appears cost-effective on average, it may not be so for the entire population of potential adopters (Jaffe and Stavins, 1994b).
4. Consumers and firms may find that two similar technologies that provide the same service are not perfect substitutes for one another (Jaccard et al., 2003).
5. Consumers and firms do not have perfect information about all different technologies available in the market, and gathering and synthesizing that information is a costly endeavour (Sutherland, 1991).

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.
All of these factors lead bottom-up models to be overly optimistic in predicting the opportunities for low cost reductions in energy-related emissions.

In contrast, top-down models use aggregated market data to predict the overall economic effect of a policy. They range from simple identity-type models to complex models that capture inter-sectoral transactions through an input-output table, with some portraying full equilibrium throughout the economy.

Top-down models include a picture of market behavior that implicitly accounts for the five factors missing from bottom-up analysis, since they are based on the observed interaction of producers and consumers in the market. However, top-down analysis is not without its challenges – most importantly in terms of capturing fully the process of technological change.

Substantial reduction of GHG emissions, in order to eventually stabilize atmospheric GHG concentrations, is a long-run objective that requires dramatic technological change over a lengthy period during which consumer preferences are also likely to evolve. Policy-makers need to know if and how their policies can influence both the long-run evolution of technologies as well as the long-run evolution of consumer preferences in ways that reduce welfare losses from switching to less GHG-intensive technologies. The key parameters in top-down models, the elasticities of substitution (ESUB), which define how easily one aggregate input can be substituted for another as their relative prices change, and the autonomous energy efficiency index (AEEI), which defines how quickly energy efficiency increases autonomously in the economy, are usually estimated from historical data. Even if the confidence intervals of these estimated parameters are narrow, there is no guarantee that values derived from past experience will remain valid into the future (Grubb et al., 2002). For example, AEEI and ESUB could change dramatically in the future as financial costs of technologies change due to economies of scale in production or accumulated experience, and as consumers become more willing to accept emerging technologies as they become better established in the market. These processes are endogenous to the market, meaning that they can be influenced by policy as well as by what else is happening in the economy. AEEI and ESUB are fixed parameters in a typical top-down model, however, meaning that such a model is unable to show the full potential adaptation of firms and households to policies that significantly affect economic conditions. This can lead to overestimates of the cost of reaching environmental goals (Buanano et al., 2003; Gerlagh and van der Zwaan, 2003).

In fairness to top-down models, significant effort has been invested in the past decade to address technological change endogenously. The most
common mechanisms for endogenous technological change are via investment in R&D in response to market conditions, spillover rates from R&D, and economies-of-learning (Loschel, 2002). While these developments improve the potential usefulness of top-down models, few researchers have thus far grappled with the challenge of empirically estimating the aggregate parameters of endogenous technological change in these models (Carraro et al., 2003; DeCanio, 2003; Loschel, 2002).

In addition to their bias towards high costs, top-down models are also restricted because of their aggregate level of analysis, which prevents the exploration of technology-oriented policies, and cannot predict the adoption of specific technologies under alternative scenarios. These questions are often of interest to policy makers, who shy away from politically unacceptable policies like economy-wide taxes and prefer technology-oriented instruments like renewable portfolio standards, subsidies, appliance regulations, and technology labelling programs (Hahn and Stavins, 1992). In other words, top-down models have considerable difficulty addressing the type of questions that policy makers are interested in.

As we move into an era where energy policy could be poised for dramatic changes in response to environmental pressures, 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 that integrate the strengths of both traditional approaches, and in so doing, overcome their weaknesses. Such hybrid energy-economy models would attempt to bridge the methodological schism between top-down and bottom-up by meshing the description of the economy in terms of specific technologies (as in bottom-up models) with the reliance on real market data to explain behavior (as in top-down models) into an integrated energy-economy model. Some attempts over the past twenty years have been made to develop this form of model (Grubb, 1993). Most models, however, did not realistically portray consumer and firm behavior at a technology-specific level. For example, the hybrid modeling attempts of Hoffman and Jorgenson (1977), Jacobsen (1998), Bohringer (1998), and Koopmans and te Velde (2001) incorporated some technological-level information, but relied on linear programming models of the energy system to determine energy prices and technology choices for what was otherwise a top-down model formulation.

In the research reported here, we describe and estimate the parameters for a hybrid model, called CIMS, that attempts to realistically capture consumer and firm behavior at the technology level, while also simulating the interaction of energy and the output of key sectors of the economy, including trade effects (Jaccard et al., 2003; Nyboer, 1997; Jaccard et al., 1996). Thus, this model covers much of the same perspective as traditional top-down models, although current

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3. Although CIMS was initially developed for Canadian applications, it is now being used in other countries.
versions do not equilibrate labour markets, capital markets, intermediate goods markets, and government budgets to the full extent of most CGE models.

This paper describes the process we have developed for empirically estimating these behavioral parameters for the CIMS hybrid model from consumer and firm technology-specific preference research. Section II describes the CIMS model. Section III describes how the data was collected and analyzed. Section IV describes the model that was produced from the data and how that model was used to estimate the three behavioral parameters in CIMS. In this section, we demonstrate how the updated CIMS model can be used for technology explicit and behaviorally realistic policy analysis. Section IV also quantitatively estimates the uncertainty around predictions from the CIMS model. In section V, we provide a discussion of the process used to estimate the parameters and summarize the usefulness of the approach.

II. THE CIMS MODEL

CIMS is an explicit technology vintage model, meaning that it tracks the evolution of technology stocks over time through retirements, retrofits, and new purchases, with consumers and producers making sequential decisions with limited foresight about the future. 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 and firms at each node. In each time period, technology stocks are retired according to an age-dependent retirement function, and demand for new technologies is assessed based on current technology stocks and either an exogenous service demand forecast or the demand for energy services that results from the interplay of the energy supply-demand module with a simplified macro-economic module. CIMS then simulates the competition of technologies at each service node in the economy by determining their market share according to the following formula:

\[ MS_j = \left( \frac{CC_j^* \cdot r + MC_j + EC_j + i_j}{1 - (1+r)^{-n}} \right)^{\frac{1}{v}} \]

\[ \sum_{k=1}^{K} \left( \frac{CC_k^* \cdot r + MC_k + EC_k + i_k}{1 - (1+r)^{-n}} \right)^{\frac{1}{v}} \]

4. 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 $MS_j$ is the market share of technology $j$, $CC_j$ is the capital cost, $MC_j$ is the maintenance and operation cost, $EC_j$ is the energy cost, $i_j$ is the intangible cost (for example, there is an intangible cost associated with public transit compared with single occupancy vehicles due to real or perceived inconvenience, lower status, longer travel time, discomfort, etc.), $r$ is the private discount rate (which is usually the same for all technologies at a given node, but which differs between nodes according to empirical research), and $v$ is a 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 as seen by consumers and firms. In this formulation, the inverse power function acts to distribute the penetration of a particular technology $j$ relative to all other technologies $k$ at the node. A high value of $v$ means that the technology with the lowest LCC captures almost the entire new market share. A low value for $v$ means that the market shares of new equipment are distributed fairly evenly, even if their LCCs differ significantly. Figure 1 is a graphical representation of the simple case where two technologies with different life cycle costs are competing for new market share with different values of $v$.

**Figure 1. Market Heterogeneity in the CIMS Model**

When the LCCs of each technology are equal (a ratio of $LCC_A / LCC_B = 1$ in Figure 1), each captures 50% of the market. When the LCC of technology A increases over that of technology B, less people choose A. At $v = 10$, when technology A becomes 15% more expensive than B, B captures 85% of the market. At $v = 1$, when technology A becomes 15% more expensive than technology B, B only captures 55% of the market. We consider this second case a more heterogeneous market, and the first case a more homogeneous market. A traditional linear programming optimization model would have $v = \infty$, equivalent...
to a step function where the cheapest technology captures 100% of the market – a completely homogeneous market.

The CIMS model essentially captures consumer and firm behavior using three parameters: (a) the private discount rate \( r \), (b) the market heterogeneity parameter \( v \), and (c) the intangible cost factor for each technology \( i \). Returning to the list explaining the problems with bottom-up models, (a) accounts for problems (1) and (2), (b) for problem (3), and (c) for problems (4) and (5).

These behavioral parameters have been estimated through a combination of literature review, judgement, and meta-analysis (Nyboer, 1997). However, the literature we have used to set our parameters has estimated the three parameters separately, sometimes using the discount rate to account for problems (1) through (5). This leads to potential problems for predicting the costs and effects of policies. To account for this, we have begun a process of empirically estimating the three parameters simultaneously from actual market behavior. Integrating this realistic description of the behavior of economic actors at a microeconomic level into a technology explicit model addresses many of the concerns that arise from using a strictly top-down or bottom-up modeling approach, and should provide more useful information to policy makers about the likely effects of alternative energy policies.

III. DATA COLLECTION AND ANALYSIS

CIMS is made up of over 1,000 technologies competing for market share at hundreds of nodes throughout the economy, to simulate the most influential energy technology decisions in the real world. Obviously, gathering information on consumer and firm choices at each of these nodes is a huge task, so we focus our efforts on gathering empirical information on consumer and firm choices at several of the most important nodes throughout the energy-economy. This paper presents an empirical study of the choice of steam generation system in industrial plants.\(^5\)

In Canada, industrial steam production represents approximately 15% of the country’s total primary energy consumption (EIA, 2003; NRCan, 2000). It is a node where a proven and well-established technology – cogeneration – offers dramatic opportunities for savings in energy use and associated emissions production (Joskow and Jones, 1983). Finally, it is also a node where many of the technologies currently in use are approaching retirement, and will need to be replaced in the coming ten to fifteen years (Klein, 2001). For these reasons, a well-developed understanding of behavior at the industrial steam generation node is critical for assessing the potential of policies to shape the way in which major energy-using firms consume energy and produce emissions.

\(^5\)Our research group has conducted simultaneous studies on personal transportation decisions and residential appliances, heating and building shell decisions. We continue to conduct research similar to that presented in this paper exploring behavior in other parts of the economy.
We used a choice experiment to gather data on the choices made by industrial plants with regard to steam generating technologies. The experiment presented respondents (in this case plant managers at industrial facilities from various sectors and regions in Canada) with alternative steam generating technologies with varying attribute levels and asked them to identify the technology that would be chosen by their firm. We chose to use stated preference data, which comes from hypothetical or survey situations in which respondents state what their choices would be in a hypothetical situation, as opposed to revealed preference data, which comes from observations of people’s actual choices and behavior in real-world situations, for several reasons. First, the explanatory variables in revealed preference data are often highly collinear and exhibit little variability in the marketplace, which can make estimating a model based on this kind of data difficult. Second, revealed preference data may have less plausibility in analyzing the impact of policies that move the economic system beyond its historic boundaries. Finally, revealed preference data are often difficult to gather due to problems with respondent recollection of purchases and decisions made years in the past. Stated preference experiments are designed by the analyst and so avoid most of these problems. However, stated preference data can be biased because when answering a survey, consumers do not face real world constraints (e.g., budgetary or information constraints). Further biases may arise if consumers do not understand the survey properly or if they purposefully bias their answers to alter the survey results (Louviere et al., 2000; Train, 2002). Research has found, for example, that consumers often demonstrate a higher affinity for energy-efficient technologies on stated preference surveys than they do in reality (Urban et al., 1996). In summary, both stated and revealed preference data can be useful sources, however, given the limited nature of rich (revealed) data on actual technology choices, we chose to use stated preference data in this experiment.

We sampled firms randomly from across all regions in Canada from the industrial sectors listed in Table 1 for inclusion in the study. Over 8,500 firms were contacted in the first phase of the survey and asked whether they used steam for process heating and, if so, whether they were willing to participate in the study. Only 1,495 of the firms contacted used process steam, and of those, 591 agreed to participate in the survey. Plant managers from these 591 firms were asked several questions regarding energy use in their plant. This information was used to customize the mailed choice experiment so that the size and fuel type of the steam generating equipment in the choice experiment matched up to the size and type used by the firm. Responses to the mailed choice experiment were received from 259 plant managers, for a 43.8% response rate to the mailed survey, and a 17.3% response rate for qualifying firms overall.6 This is normal for a survey of business.7 We found that a slightly greater proportion of large firms participated in the study than small firms. This is likely a reflection

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6. We received 295 responses from 1,495 relevant firms initially contacted for a total response rate of 17.3%.

7. This is normal for a survey of business. We found that a slightly greater proportion of large firms participated in the study than small firms. This is likely a reflection...
of their greater capacity to respond to surveys as well as of the higher importance of steam to the operations of large firms than to small firms. Similarly, we found a higher response among firms in the three sectors that account for the bulk of the cogeneration activity in Canada (SIC 26, 28, and 29).8

Table 1. Industrial Sectors Included in Survey (US SIC system)

<table>
<thead>
<tr>
<th>SIC</th>
<th>Sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>Food and Kindred Products</td>
</tr>
<tr>
<td>22</td>
<td>Textile Mill Products</td>
</tr>
<tr>
<td>24</td>
<td>Lumber and Wood Products, Except Furniture</td>
</tr>
<tr>
<td>26</td>
<td>Paper and Allied Products</td>
</tr>
<tr>
<td>28</td>
<td>Chemicals and Allied Products</td>
</tr>
<tr>
<td>29</td>
<td>Petroleum Refining and Related Industries</td>
</tr>
<tr>
<td>30</td>
<td>Rubber and Miscellaneous Plastic Products</td>
</tr>
<tr>
<td>31</td>
<td>Leather and Leather Products</td>
</tr>
<tr>
<td>33</td>
<td>Primary Metal Industries</td>
</tr>
<tr>
<td>35</td>
<td>Industrial and Commercial Machinery</td>
</tr>
<tr>
<td>38</td>
<td>Measuring, Analyzing, and Controlling Instruments; Photographic, Medical, and Optical Goods; Watches and Clocks</td>
</tr>
</tbody>
</table>

The survey presented respondents with four hypothetical choice situations in which the respondent was asked to choose between a standard efficiency boiler, a high efficiency boiler, and a cogeneration system. Each technology was characterized by attributes for capital cost (CC), operation and maintenance cost (OC), fuel cost (FC), and value of electricity produced (EP) (only cogeneration systems are able to produce any electricity), which were varied according to the statistical design described below.9 Attribute levels were customized to the characteristics of each firm (the quantity of steam and electricity required, the required steam pressure, and the type of fuel used) based on responses to the telephone survey. For example, if the firm being surveyed was a small food cannery that used natural gas for its steam requirements, the attributes of potential boilers and cogeneration systems would be much different than if the firm being surveyed was a large petroleum refinery that burned still gas to produce steam. To keep the survey tractable for respondents, we assumed that future boiler or cogeneration...

7. In a review of 183 business surveys, Paxson (1995) reports that the average response rate was 21%. A similar study of industrial energy efficiency in the Netherlands received a response rate of only 4.2% (de Groot et al., 2001), while a Canadian study on energy efficiency in industry received a response rate of 15% (Takahashi et al., 2001).

8. Petroleum refineries (SIC 29), chemical manufacturers (SIC 28), and pulp and paper mills (SIC 26) are responsible for over 75% of the cogeneration capacity in Canada (MK Jaccard and Associates, 2002).

9. Including a greater number of parameters in our model specification would have been possible, and might have led to a more accurate characterization of decision making in industry. However, we note that we chose the included variables based on detailed interviews with plant managers and boiler/cogeneration consultants, and these represent the most significant attributes for technology choice.
systems would use the same type of fuel used in each plant as the primary boiler fuel. As such, we cannot estimate preferences for different fuel types. To inform respondent choices, the choice experiments included a payback period analysis and net present value (NPV) curves, comparing the high efficiency boiler and the cogeneration system with the standard efficiency boiler. A copy of the survey can be obtained from the authors on request.

The statistical design we used had four different levels for capital cost and fuel cost, and two each for operating cost and electricity production. Each level is a multiplier for the appropriate “base case” attribute value, determined from responses to the telephone survey and the CIMS technology database. Ideally, for each unique combination of CC, OC, FC, and EP, choices of several different firms would be observed. This would enable estimation of how choice outcome is affected by changes in one attribute while all others are held constant, as well as how choice outcome is affected by one or more variables changing in combination. However, to test four levels for capital cost and fuel cost, and two for operating cost and electricity savings, obtaining six observations (recommended by Louviere et al. (2000) as a rule of thumb for stated preference surveys) for each of these combinations of attribute levels would require $6 \times 4^4 = 393,216$ observations (this is referred to as a $2^{16}$ full factorial design). Such a large amount of observations were obviously not obtainable, so instead we used a 1/2048th fractional factorial design, where observations are only obtained at key combinations of attribute levels.\textsuperscript{10}

We used a linear-in-parameters utility function to represent the choices of plant managers, as in Equation 2.

$$U_j = \beta_j + \sum_{k=1}^{K} \beta_k x_{jk} + \epsilon_j$$

Where $U_j$ is the utility of technology $j$, $\beta_j$ is the alternative specific constant, $\beta_k$ is a vector of coefficients representing the importance of attribute $k$, $x_{jk}$ is a vector of the $k$ attributes of technology $j$, and $\epsilon_j$ is the unobservable error term. Based on the attributes included in the survey, Equation 2 can be represented specifically for this survey as Equation 3.

$$U_j = \beta_j + \beta_{CC} CC_j + \beta_{OC} OC_j + \beta_{FC} FC_j + \beta_{ES} EP_j + \epsilon_j$$

By assuming that the unobserved error terms ($\epsilon_j$) are independent and identically distributed Type 1 Extreme Value, we can generate a model of the probability of a firm choosing technology $j$ from the available set of technologies, $K$. This is called the multinomial logit (MNL) model (Train, 2002):

\textsuperscript{10} This fractional factorial is said to be of resolution IV, which means that main effects are confounded with third-order interactions. Such a confounding pattern is generally not of concern when main effects are of most interest, and can be thought of as initiating up to a 1% error into main effects estimates as a rule of thumb (Montgomery, 1991; NIST/SEMATECH, 2001).
The Energy Journal

\[ P_j = \frac{e^{U'_j}}{\sum_{k=1}^{\Sigma} e^{U'_k}} \]  (4)

Where \( U' \) is simply the observable portion of utility, and \( U' = U_j - e_j \).  

We then use a maximum likelihood routine to find the \( \beta \) parameters that most closely match the left hand side to the right hand side of equation 4 for the set of observations. In other words, we find the parameters for which the model best matches the actual choices firms indicated in their survey responses.

After estimating the maximum likelihood parameters for the MNL model, we turned to estimating the CIMS parameters from the MNL model. The implicit discount rate applied by a consumer in a decision can be determined by comparing the capital cost parameter with any annual cost parameters (Train, 1985; Train, 2002).

\[ r = \frac{\beta_{CC}}{\beta_{AC}} \]  (5)

Where \( \beta_{AC} \) is a parameter representing the importance of all annual costs together, including fuel cost, operation and maintenance cost, and offset electricity costs. Similarly, the (annual) intangible cost parameter can be calculated by comparing any non-cost parameters to the annual cost parameters. This parameter shows the monetary cost of the intangible (non-financial) qualities of each technology. For example, on average, consumers might be willing to pay $400/year extra to drive a car, and avoid the (real or perceived) discomfort of riding a bus.

\[ t_j = \frac{\beta_j}{\beta_{AC}} \]  (6)

The final CIMS behavioral parameter (\( \nu \)), representing the degree of heterogeneity in the market, is roughly equivalent to the “scale” of the MNL model (see Train (2002) for a discussion of model scale). If the error terms (\( e_j \)) are comparable in magnitude to the parameter (\( \beta_j \) and \( \beta_{k*}x_{jk} \)) values, the model shows a more heterogeneous market where the error term plays a dominant role.

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11. Discrete choice literature usually denotes the observable portion of utility as \( V_j \). We call it \( U'_j \) to avoid confusion with the CIMS \( \nu \) parameter (equation 1).

12. We considered embedding the MNL models (Equation 4) directly into the CIMS model, effectively bypassing the CIMS algorithm (Equation 1). However, because we have not initially set out to develop empirical estimates for technology choice at each node, this would have led to a more inconsistent and opaque model.

13. Equation 5 is valid in the case where the lifespan of the technologies is long (\( > ~15 \) years), which is the case for steam generating technologies.
in predicting technology choices. Since the error term is not known, even where one technology appears to have a clear advantage over others, the presence of a large error term can lead to the other technologies capturing a significant portion of the market. In contrast, if the error terms are much smaller than the parameter values, the model shows a much more homogeneous market, where predictions of technology choices are strongly dependent on the relative attributes of the technologies. Unfortunately, although both the CIMS and MNL models show similar logistic curves of technology adoption, they are different enough that it is not possible to directly estimate the CIMS heterogeneity factor from the scale of the MNL model. It is possible, however, to numerically find the value of \( v \) for which predictions from the DCM are consistent with predictions from the MNL model over a broad range of scenarios. We used ordinary least squares (OLS) to find the value of \( v \) that corresponds to the scale of the MNL model.

IV. RESULTS

Discrete Choice Model

Attribute coefficients for the discrete choice model were estimated using continuous attribute coding with LIMDEP 7.0. The discrete choice model was based on responses to the choice experiment from all 259 respondents to the survey. With four choice experiments on each survey, a total to 976 data points were obtained for estimation. Coefficient estimates and statistical significance (t-test values) for the discrete choice model (Equation 3) are presented in Table 2.

Table 2. Discrete Choice Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>t-value</th>
</tr>
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<tbody>
<tr>
<td>Capital Cost (SM)</td>
<td>-0.216</td>
<td>-2.924**</td>
</tr>
<tr>
<td>Operating Cost (SM)</td>
<td>-0.0967</td>
<td>-0.064</td>
</tr>
<tr>
<td>Fuel Cost (SM)</td>
<td>-0.151</td>
<td>-1.325***</td>
</tr>
<tr>
<td>Electricity Produced (SM)</td>
<td>0.687</td>
<td>8.051**</td>
</tr>
<tr>
<td>Constant – Standard Efficiency Boiler</td>
<td>-0.261</td>
<td>-2.110**</td>
</tr>
<tr>
<td>Constant – High Efficiency Boiler</td>
<td>0.225</td>
<td>2.320**</td>
</tr>
<tr>
<td>( L(0) )</td>
<td>-1072.245</td>
<td></td>
</tr>
<tr>
<td>( L(a) )</td>
<td>-1065.201</td>
<td></td>
</tr>
<tr>
<td>( L(\beta) )</td>
<td>-1016.098</td>
<td></td>
</tr>
<tr>
<td>( L(\beta)/N )</td>
<td>-1.042</td>
<td></td>
</tr>
<tr>
<td>(-2*(L(\beta) – L(0))) ( \chi^2 )</td>
<td>112.294 with 6 d.o.f.*</td>
<td></td>
</tr>
<tr>
<td>(-2*(L(\beta) – L(a))) ( \chi^2 )</td>
<td>98.206 with 4 d.o.f.*</td>
<td></td>
</tr>
<tr>
<td>( \rho = 1 – L(\beta)/L(0) )</td>
<td>0.0524</td>
<td></td>
</tr>
</tbody>
</table>

* Both of these Chi-squared tests are significant at the 99.9% confidence level.
** Coefficient significant at 95% confidence level
*** Coefficient significant at 80% confidence level
Based on significance levels, the non-fuel operating cost coefficient was the only parameter that seemed to not affect respondent choices. This is not surprising, because in general the non-fuel operating cost was dwarfed by other costs in the choice experiment, and so probably had less influence on the choice outcome than the larger costs. For example, for a typical 12 MW natural gas boiler, annual operating cost is just 4% of the capital cost and 16% of the annual fuel cost.

As should be expected in a stated preference choice experiment, all attribute coefficients are of the correct sign; increases in capital, operating, or fuel cost all decrease utility, while increases in electricity production increase the utility. The alternative specific constants capture the systematic preferences by respondents for particular technologies, independent of the attributes that were tested for – in this experiment they essentially capture non-financial cost attributes. The estimated alternative specific constants show that standard efficiency boilers are less preferred than cogeneration (which has an alternative specific constant of 0), while high efficiency boilers are more preferred than both cogeneration and standard efficiency boilers if all costs are held equal for the three technologies.

Some insight into the reason for the signs of the alternative specific constants can be gained from respondents’ answers to one of the qualitative questions in the survey that sought to understand how plant managers perceive cogeneration systems as compared with boilers. Figure 2 shows that while respondents do not feel there is a significant difference between boilers and cogeneration systems in terms of safety or reliability, they feel that boilers outperform cogeneration systems in terms of cost and ease of maintenance, while the opposite is true in terms of environmental impact. It is likely, then, that the negative alternative specific constant for standard efficiency boilers is due to their perceived environmental impact, while the positive alternative specific constant for high efficiency boilers is due to the fact that plant managers perceive that boilers are easier maintained than cogeneration systems (the high efficiency boilers have a lower environmental impact than standard efficiency boilers).
Figure 2. Comparison of Cogeneration System with Boiler

Note: 1 indicates that the respondent feels a cogeneration system is "Much Worse" than a boiler in the category specified, while a 5 indicates that the respondent feels a cogeneration system is "Much Better" than a boiler in the category specified.

For policy analysis, it is important to understand how the predicted choice probability of an alternative changes in response to a change in the value of one of the attributes. For example, it might be necessary to know how much the probability of choosing a cogeneration system would increase as its capital cost decreased (due to a subsidy for example). In order to answer this type of question, the first partial derivative of the choice probability is calculated – this value shows the change in choice probability per change in attribute value:

\[
\frac{\partial P_i}{\partial (e^V_i/\sum_j e^V_j)} = \beta_z P_i (1 - P_i) 
\]

Table 3 shows the change in choice probability of each alternative given a $1,000,000 increase in attribute value. We call this value a responsiveness. For example, if the capital cost of the standard efficiency boiler were increased by $1,000,000, we would expect to see a 4.77% decline in the new market share of the standard efficiency boiler.

14. Of course, the elasticity estimates we present are dependent on the estimated model being the correct one (i.e., not suffering from omitted variable biases).

15. The responsivenesses are calculated starting from base attribute levels for a technology with 12 MW steam output capacity. Technology attribute values used in this study can be obtained from the authors.
Table 3. Responsiveness Estimates

<table>
<thead>
<tr>
<th>Technology</th>
<th>Effect of a $1,000,000 increase in:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Capital Cost</td>
<td>Operating Cost</td>
</tr>
<tr>
<td>Standard Efficiency Boiler</td>
<td>-0.0477</td>
<td>-0.0214</td>
</tr>
<tr>
<td>High Efficiency Boiler</td>
<td>-0.0517</td>
<td>-0.0231</td>
</tr>
<tr>
<td>Cogeneration System</td>
<td>-0.0430</td>
<td>-0.0193</td>
</tr>
</tbody>
</table>

Table 3 reveals two lessons regarding relative attribute importance that are critical to effective policy design. First, by comparing the capital cost responsiveness to the annual cost responsiveness estimates, we see that manipulating the capital cost through policy is generally a more effective way to affect choices than manipulating the annual costs (except changes to the electricity production). If, for example, a subsidy were used to encourage cogeneration, a $1,000,000 capital cost subsidy would increase the new market share of cogeneration by 4.3%, while a $1,000,000 fuel cost subsidy would only increase the new market share by 3.0%. Further, the fuel cost subsidy would need to be paid every year while the capital cost subsidy would only need to be paid in the year of equipment purchase. At a social discount rate of 10%, the hypothetical fuel subsidy has an NPV of about $9,000,000 over a 30-year project lifetime, about nine times the total cost of the capital subsidy. The result that subsidies that reduce up-front costs are more effective than policies that affect annual costs is well established in the literature (Jaffe and Stavins, 1995; Hasset and Metcalf, 1995).

Second, in comparing the three annual cost responsiveness estimates (operating cost, fuel cost, and value of electricity production), we see that the highest leverage point for policy is manipulating the value of electricity production, rather than the fuel or operating costs. A $1,000,000 increase in electricity purchase savings affects the choice probability over six times as much as an equivalent savings in operating costs, and over four times as much as equivalent fuel cost savings. Most bottom-up analyses of cogeneration (and other technologies) assume that firms are indifferent to a $1 increase in fuel costs versus a $1 increase in operating and maintenance costs. The model estimated here, however, shows that firms feel differently about different types of costs; in particular, they value savings from on-site electricity production very highly. A possible reason for the premium that firms place on reducing electricity purchases is the value they place on some degree of independence from grid-provided electricity, whose price they have no control over. Cogeneration provides firms with somewhat more control over the price they pay for electricity by insulating them from potential spikes in centralized grid prices. Cogeneration can act as a backup power provider to limit a firm’s exposure to centralized grid outages, reducing potential for electricity outages in the firm.
The analysis described in the previous section is relatively simplistic as measured by the standards of applied discrete choice modelers. Internationally, much fruitful research is being conducted on various choices of energy-using technologies using probit, generalized extreme value, and mixed logit models, among others (e.g., Hausman (1979), Revelt and Train (1998), Bunch et al. (1993), Goett et al. (2000), Stavins (1999)). Each of these more complex functional forms relaxes some or all of the assumptions inherent in multinominal logit models and should ultimately improve the information available to policy makers.

However, while sophisticated DCMs provide a reliable means to predict technology choice on a single-technology level, they are of limited use to policy makers on their own 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 the purchase of efficient appliances would be potentially 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. Accounting for these interacting effects is particularly important for exploring climate change policy, when overlapping policies will likely be implemented simultaneously throughout the economy.

Using the results of DCMs in a hybrid model allows for these interacting effects to be included in the analysis. Following the methodology described above, we estimated the behavioral parameters in the CIMS model from the results of the DCM. Table 4 shows that we estimated a discount rate of 34.7%, and annual intangible costs of $500,000 for the standard efficiency boiler and -$137,000 for the high efficiency boiler. These intangible costs were estimated independent of steam output, meaning that they are an important factor for small systems, and a relatively negligible factor for very large (>50 MW) systems. 16 We estimated the market heterogeneity factor at 1.4, which implies that the market is quite heterogeneous, with technologies that are apparently cost-effective for one firm not necessarily so for another.

16. Although it would have been interesting to estimate intangible costs as a function of steam output, our data set was not large enough to enable statistically significant model segmentation.
Table 4. CIMS Behavioral Parameters Estimated from the DCM

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount Rate (r)</td>
<td>34.7</td>
</tr>
<tr>
<td>Intangible costs (i)</td>
<td></td>
</tr>
<tr>
<td>Standard Efficiency Boiler</td>
<td>$500,000</td>
</tr>
<tr>
<td>High Efficiency Boiler</td>
<td>-$137,000</td>
</tr>
<tr>
<td>Cogenerator</td>
<td>$0</td>
</tr>
<tr>
<td>Market Heterogeneity (v)</td>
<td>1.4</td>
</tr>
</tbody>
</table>

While other studies have not attempted to calculate parameters like market heterogeneity or intangible costs of alternative steam generation technologies in the same way as we have here, many studies use the discount rate parameter to characterize the choice of energy efficient technologies, so we can compare our estimated parameters to those found in other research.

Some analysts suggest that high discount rates on energy investments, as we have calculated here, are inconsistent with proper market function (they exceed return to common stocks by a factor of three or more, exceed rates of return to public utilities, and exceed lending rate offered by credit cards by a factor of two or more), and should therefore be discredited (DeCanio and Laitner, 1997). However, the bulk of the literature on private-sector decision making with regards to energy projects finds that high discount rates found in empirical studies are likely a reflection of the reality of obtaining information in the market, the difficulties of collective action within a firm, the high perceived risk of energy efficiency investments, the skepticism of company decision makers to *ex ante* claims of high rates of return on energy efficiency investments, the option value of waiting for more information before making a decision, and the limited time available to top decision makers to evaluate energy saving technologies, among other factors (Harris et al., 2000; Dixit and Pindyck, 1994; Sassone and Martucci, 1984; de Groot et al., 2001; Hasse and Metcalf, 1994). Train (1985) summarizes several studies on discount rates using similar methodologies to that used in this paper, and finds results ranging from 15% to 70% in the residential sector (a similar survey article was not found for the industrial sector). The discount rate calculated in this study is consistent with this latter stream of literature.

*Policy Analysis Using CIMS*

With the parameters of CIMS estimated empirically, we demonstrate the use of CIMS by simulating the effect of policies aimed at increasing the energy-efficiency of industry, in particular through the promotion of cogeneration systems over boilers for steam generation. We examine the effects of three hypothetical policies:

- **Capital cost subsidy** on cogeneration technologies – a subsidy of 20% of the capital cost of all cogeneration systems to encourage cogeneration.
• **Tax on carbon dioxide** emissions – a $50/tonne CO₂e tax to reduce GHG emissions. Such a policy should increase the amount of cogeneration because the overall emissions of cogeneration are generally lower than for separate production of heat and power, although this depends on what happens throughout the economy, especially in the electricity generation sector, in response to the policy.

• **Information provision** to diffuse knowledge of cogeneration – we determine the effect of the information program by segregating the discrete choice model described in the previous section into one group of respondents who indicated that they were “well-informed” about technical, financial, and regulatory issues regarding cogeneration and another group who were not. We then assume that an information program will cause the second group to behave identically to the first group.

Figure 3 presents the results of our policy simulations in CIMS, and shows the evolution in the market share of cogeneration in Ontario (largest province in Canada) over time under different policy scenarios. CIMS is a technology vintage model, so policies do not immediately impact all capital stock, but rather influence purchase of new stock as old technologies turn over (and in some cases cause premature retirement or retrofit of existing stock). Information provision increases the new market share of cogeneration by about 5% over business as usual, while the $50/tonne of CO₂e tax increases the new market share of cogeneration by 6-10% over business as usual. The subsidy has the largest effect on the new market share of cogeneration, increasing it by 19-26% over business as usual.

**Figure 3. Policy Analysis Using CIMS**

![Graph showing the impact of different policies on cogeneration market share.](image)

This comparison of policy alternatives is somewhat superficial because we have ignored the cost side of the policy analysis, focusing only on the benefits of the policies. However, the policies we have chosen to simulate...
are not directly comparable in terms of cost, with the tax influencing welfare throughout the entire economy to a greater degree than the other two policies, and the information program consisting of government expenditures rather than consumer welfare changes. Consequently, Figure 3 does not imply that subsidy programs are more effective than taxes or information programs, a conclusion that could only be drawn through an evaluation of both the costs and benefits of the policies.\textsuperscript{17}

In other research we evaluate the costs of alternative policies (Jaccard et al., 2003). The purpose of this paper is to demonstrate an empirical method for incorporating behavioural realism into a technologically detailed hybrid model, so we avoid a lengthy policy evaluation.

\textit{Treatment of Uncertainty}

The preceding policy analysis was conducted under the assumption that all behavioral parameters estimated from the DCM were free of uncertainty. In reality, however, the DCM parameters are only the single most likely estimates of the model parameters from the data. There are many other parameter values that are also possible, albeit with less probability than the maximum likelihood parameters. Ignoring the potential that these alternative parameters are correct can lead to biased and incorrect modeling results and consequent policy recommendations. Including an analysis of uncertainty not only avoids implying an undue sense of confidence in the model, it also allows the modeller to determine the areas ripe for the most fruitful future research, and helps to identify the most important factors to consider when making a decision (Morgan and Henrion, 1990).

In order to account for the uncertainty in our model, we constructed a six-dimensional joint probability density function (pdf) for the model parameters from equation 8:

\[
LL(\beta) = \sum_{n=1}^{N} \frac{\ln (P_{n,j}(\beta))}{N}
\]

Where \( LL(\beta) \) is the log of the likelihood for the parameters \( \beta \), \( N \) is the number of observations in the data set, and \( P_{n,j}(\beta) \) is the probability that the model assigns to the choice \( j \) that was actually made by the respondent at observation \( n \) with the particular combination of \( \beta \) parameters being tested. \( P_{n,j}(\beta) \) is calculated using the multinomial logit model (equation 4).

\textsuperscript{17} Specifically, we note that our studies, as well as those of others, have found that free-rider rates on subsidy programs are often as high as 60-70\%, which implies that although the subsidy policy we have modeled here is shown to be quite effective, it is also likely to be the highest cost policy to implement.
We then sampled uniformly from this probability density function for the six DCM parameters. Each point on the probability density function was characterized by six parameter values (each parameter of the discrete choice model of equation 3) and a probability. From the six parameter values, we were able to calculate the CIMS parameters at each point using the method described in preceding sections, and subsequently construct marginal probability density functions for each of the CIMS parameters. We then propagate the uncertainty in the parameter values through the CIMS model through a simplified sampling procedure.

Figure 4 shows the results of this exercise for one of the three policies that we examined – the 20% capital cost subsidy on cogeneration. While the simulation results using the MLE parameters predict an increase in cogeneration market share of about 20-25% over business as usual, the 95% confidence intervals show that we could expect an increase of anywhere from about 12-36% over the 30-year simulation period. Clearly, a policy analysis based only on the MLE parameters does not fully reflect uncertainty in the data set.

Moreover, the uncertainty portrayed in Figure 4 does not fully represent the uncertainty associated with this modeling exercise. It only represents the uncertainty associated with the behavioral parameter estimates given that the data set is a perfect representation of firm behavior. The data set is unlikely to fully represent firm behavior because of the combination of:

- coverage error, in which a sample is drawn from an incomplete subpopulation and subsequently extended to the population as a whole;
- non-response error, in which participants who are removed from the population (either through not qualifying for the survey, or by refusing to participate) bias the survey results;
• sampling error, in which the results of a sample of the population are inferred to represent the whole population; and
• measurement error, in which respondents misinterpret the questions on the survey questions, or do not answer the questions truthfully (Dillman, 2000).

Further uncertainty exists not only in the representation of behavior, but also in the representation of technology. Costs for the various steam generating technologies were assessed several years ago for CIMS and may be somewhat unrepresentative today. Because of the combination of these errors, the confidence intervals presented in Figure 4 should be taken as a lower bound on the amount of uncertainty present in this exercise.18

V. CONCLUSIONS

Previous generations of energy-economy models – traditional bottom-up and top-down models – may be limited in their usefulness to policy makers. In particular, top-down models do not explicitly represent the technologies in the energy system, so policies designed to influence technology evolution directly can only be crudely simulated at best. Bottom-up models are based on theoretical assumptions about human behavior, with the result that their predictions are unrepresentative of the economic system. A new generation of hybrid energy-economy models contains both an explicit representation of the technologies in the economic system and a realistic representation of behavior. Such a model is based on a complete database of the technologies in the energy-economy system and requires information to indicate how consumers in the economy choose between the various technologies available for meeting their needs. Discrete choice models are well suited to provide this information in that they convert market data into relationships between the characteristics of a technology and the probability of that technology being chosen. Discrete choice models can therefore be useful in improving the empirical basis of hybrid models, which are behaviorally realistic and technologically explicit.

This paper has used discrete choice research to estimate empirically the behavioral parameters of one node in a hybrid energy-economy model. Other past and on-going research by us and others has (and will) be used to estimate parameters at other important nodes throughout the economy using a similar method to that described here. Because the resulting hybrid model is able to account for complex feedbacks in the energy-economy system, it should be more useful to policy makers than either stand-alone discrete choice models or traditional types of energy-economy models. Further research should explore the

18. To construct the confidence intervals in Figure 4, we assume that our current characterization of behavior and technologies remains valid in the future. One referee noted that in econometric studies, uncertainty increases as predictions are made outside the bounds of the data set. We acknowledge that our estimates of uncertainty should increase over time, but because of model construction, our uncertainty estimates remain constant through time.
application of more sophisticated and reliable discrete choice models covering a wide range of technology choices to estimating the parameters of hybrid energy-economy models. Such a model would thus apply rigorous empirical estimates of the way people behave to shape energy and economic policies.

The use of empirical consumer choice information allows for a quantitative understanding of the uncertainty in the model. Representing uncertainty explicitly allows the model results to be compared to those of other models, points the appropriate direction for future research, and signals the most important factors to consider in decision making.

Although we have not addressed it in this paper, we note that a detailed representation of technologies allows an energy-economy model to explicitly simulate certain elements of endogenous technological change. The CIMS model, for example, uses a learning-by-doing methodology to link the cumulative production of a technology to its capital cost, and a learning-by-using formula to link the market share of a technology to the intangible costs of the technology. These learning dynamics both depend on a realistic engine to simulate the manner in which consumers and firms in the economy choose technologies to meet their needs, which we have developed in this paper.

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