

**BEHAVIOURAL REALISM IN A TECHNOLOGY EXPLICIT ENERGY-ECONOMY MODEL: THE  
ADOPTION OF INDUSTRIAL COGENERATION IN CANADA**

by

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### Title of Project

**Behavioural realism in a technology explicit energy-economy model: The adoption of industrial cogeneration in Canada**

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## **Abstract**

Traditional models to explore the effects of environmental energy policies suffer from fundamental theoretical weaknesses that limit their usefulness to policy makers. In particular, top down models lack technological detail and so cannot be used to fully explore policies influencing technology diffusion. Their traditional alternative, bottom-up models, lacks behavioural realism and so cannot be trusted to realistically simulate outcomes in the energy economy.

In the past two decades, hybrid models have emerged with the objective of overcoming the weaknesses of the traditional energy models. Hybrid models essentially merge bottom-up and top-down methodologies and so require an understanding of consumer behaviour at the technological level. Discrete choice models can provide this technology specific behavioural information to hybrid models.

This paper demonstrates how discrete choice models can be used to inform the behavioural parameters of a hybrid model by estimating a discrete choice model of the industrial steam generation technology decision. A survey of 259 industrial firms in Canada was administered in 2002 and a discrete choice model was estimated from the results. The model showed that industrial cogeneration is a relatively unknown technology to many firms. Among those that were familiar with cogeneration, its high capital cost often limited its appeal. The survey results also revealed that the electricity savings offered through a cogeneration system are valued extremely highly by firms.

A policy analysis conducted using the discrete choice model's results for setting behavioural parameters in a hybrid energy-economy model revealed that an information campaign to increase knowledge of cogeneration would increase the new market share of cogeneration by about 2% over business as usual. A \$50/tonne of CO<sub>2e</sub> tax would increase the new market share of cogeneration by up to 4% over business as usual, while a 20% subsidy on the capital cost of cogeneration would increase its new market share by 6-8% over business as usual. An empirical uncertainty analysis conducted on these

results shows that we can be 95% confident that the true new market shares are not more than 3% above or below the predicted market shares.

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## Abbreviations

AEEI	Autonomous energy efficiency improvement
ASC	Alternative specific constant
BAU	Business as usual
CC	Capital cost
CGE	Computable general equilibrium
CIPEC	Canadian Industry Program for Energy Conservation
CO <sub>2e</sub>	Carbon dioxide equivalent
COG	Cogeneration system
CRF	Capital recovery factor
DCM	Discrete choice model
ES	Electricity savings
ESUB	Elasticity of substitution
FC	Fuel cost
GEV	Generalized extreme value
GHG	Greenhouse gas
GW	Gigawatt (10 <sup>9</sup> watts)
HEB	High efficiency boiler
HPR	Heat to power ratio
IPCC	Intergovernmental Panel on Climate Change
LCC	Life cycle cost
MNL	Multinomial logit
MW	Megawatt (10 <sup>6</sup> watts)
NPV	Net present value
OC	Operating cost
PURPA	Public Utilities Regulatory Policy Act
RP	Revealed preferences
SEB	Standard efficiency boiler
SIC	Standard Industrial Classification

SP Stated preferences  
VCR Voluntary Challenge and Registry

# 1. Project Rationale

## *1.1 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 environmental policies, and, particularly in the past decade, climate change mitigation policies. Because of their different structures, the two types of models tend to predict very different economic outcomes. 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 costs<sup>1</sup>. This wide spread in modelling results is confusing to policy makers, and although interesting academically, ultimately decreases the practical value of such models in real-world policy analysis<sup>2</sup>.

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

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<sup>1</sup> 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.

<sup>2</sup> 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 modelling results.

new generation of energy-economy models that integrate the strengths of both approaches.

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 mesh the description of the energy system in terms of specific technologies (as in bottom-up models) with the reliance on real market data to explain behaviour (as in top-down models) into an integrated energy-economy model.

To develop such a hybrid model, it is necessary to understand how agents in the economy make choices about how to purchase and use the technologies available to them to meet their needs. The aim of this paper is to apply discrete choice models, an existing methodology for understanding the decision making process of an economic agent, to provide a firmer empirical foundation for the behavioural parameters of a hybrid model of the Canadian economy. Specifically, this paper describes results of a discrete choice study aimed at understanding how industrial plant managers select technologies that provide the steam required in their plants. The results of this research are then integrated into a model describing the entire Canadian energy economy. This model is used to examine policies aimed at decreasing the production of greenhouse gases resulting from the production of steam and electricity for industry.

The first chapter of this paper begins by providing a general overview of energy-economy models, with a focus on the bottom-up / top-down debate. Hybrid models are then introduced, and several such models are discussed. Included in the discussion of hybrid models is a discussion of shortcomings of previous efforts at hybrid modelling. Discrete choice models are presented as a means to remedy some of the shortcomings of previous hybrid models. Using discrete choice models to estimate the behavioural parameters of a hybrid model provides a stronger basis for these parameters and should thus improve its usefulness to policy makers.

## ***1.2 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; Jaccard et al. 2003).

**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’ (financial 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 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 real-world observation, preferably originating from rigorous application of statistical inference, 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<sup>3</sup>.

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).

**Top-down models** use aggregated market data to predict the overall economic effect of a policy. Two main classes of top-down models exist: (i) time-series econometric models, and (ii) computable general equilibrium (CGE) models (IPCC 1996; Carraro and Hourcade 1998). Time-series econometric models are based on econometrically-estimated relationships and are most useful for short to medium term forecasts. In simplest terms, time-series econometric models extrapolate from past market behaviour to predict future market outcomes. They can employ detailed input-output tables to capture intra-sectoral transactions or can be simple one-equation models. A simple example of a top-down time-series econometric model is given in the box below.

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<sup>3</sup> Because the Canadian economy is to a large degree integrated with the much larger American economy, Canadian commodity prices are generally stable even when the Canadian economy is internally disturbed by a new policy. Consequently, partial equilibrium models are often used to represent the Canadian energy system (McKittrick 1998).



A CGE model is composed of a set of submodels of the various markets in the economy. Each market is assumed to clear perfectly through the movement of commodity prices until supply equals demand. The price-responsiveness of producers and consumers in the markets is defined by aggregate utility functions, which are derived from benchmark or econometric data (Bernow et al. 1998). CGE models are designed so that they find a unique optimal solution to any given scenario, and are most useful for long run modelling studies, after the economy has come to structural equilibrium following a disturbance.

Because they are based on empirical data about aggregate market behaviour, top-down models are generally considered to be more behaviourally realistic<sup>4</sup>. Top-down models can also incorporate macroeconomic effects<sup>5</sup>. 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 financial 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 modelling macroeconomic effects of policies, usually limiting their scope to partial equilibrium within the energy sector. A simple example of a bottom-up model is given in the box below. Figure 1 is a

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<sup>4</sup> Top-down models exist on a spectrum of behavioural realism. In particular, CGE models are considered less behaviourally realistic because the producer and consumer utility functions are not based entirely on market data, and often rely instead on the theory of profit maximization (Bernow et al. 1998, Laitner et al. 2001).

<sup>5</sup> CGE models fully incorporate macroeconomic effects while time-series econometric models may or may not incorporate macroeconomic effects.

conceptual representation of the different strengths of top-down and bottom-up models in the three dimensions discussed.

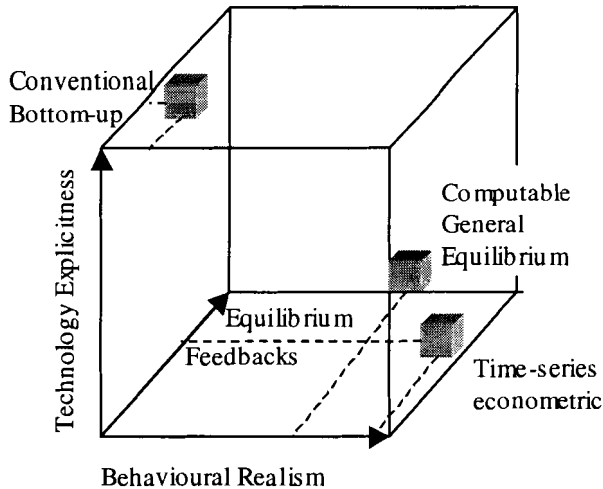
### **Examples of contrasting modelling frameworks**

#### ***Top-Down (Time-series econometric)***

Suppose we are interested in understanding the effect of a tax on greenhouse gas on the production of greenhouse gases in the economy. A simple top-down model might collect data on the consumption of oil, the price of oil, and the greenhouse gas emissions resulting from the consumption of oil between 1950 and 1990. It would then use regression analysis to formulate a relationship between the price of oil and the consumption of oil and resulting greenhouse gas emissions. Based on this relationship, the top-down model would attempt to predict the change in consumption of oil and emissions of greenhouse gases as the price of oil changed due to the tax. Note that the top-down model does not explicitly account for the future evolution of technology in the market. Historical behaviour, however, is implicitly embedded in the model since it is based on real market data.

#### ***Bottom-Up***

Suppose we are interesting in exploring the effect of a subsidy on hybrid cars on the adoption of hybrid cars, as well as the resulting shift in greenhouse gas production due to reduced fossil fuel consumption from personal transportation. A simple bottom-up model would collect cost and emissions data on all the different transportation options available to commuters, as well as new and emerging transportation technologies. It would then forecast how consumers would choose between the technologies, generally based on the assumption that consumers choose the least-cost options available to them. Simply adding the emissions from all the technologies in use in the economy shows what the total emissions in the economy would be. Note that while the bottom-up model explicitly models the evolution of technology in the market, it makes an over-simplified assumption about consumer behaviour.



**Figure 1 - Conceptual representation of conventional energy-economy models**

*Source: Adapted with permission from Jaccard et al. 2002*

The structures of both top-down and bottom-up models contribute to certain weaknesses and 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 observed market outcomes represent the optimal allocation of resources (Laitner et al. 2001). By definition then, any divergence from this equilibrium (e.g., policy induced) 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 parameters in top-down models. This is problematic when the models are used to probe scenarios of the future that diverge widely from the past because changes in economic and environmental conditions influence consumer behaviour (Norton et al. 1998), which in turn may influence future AEEI and ESUB values. Treating these parameters as static limits the

degree to which a changing environment influences both behaviour and technological evolution in the model. This is particularly problematic because the magnitude of our current environmental goals (e.g., stabilizing concentrations of CO<sub>2e</sub> 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). To achieve these goals without incurring an extremely high cost, ESUB and AEEI values will need to be substantially higher in the future than they have been in the past. Non-price policies (for instance regulations that result in otherwise unrealized economies-of-scale or economies-of-learning for certain technologies) could produce these higher values of ESUB and AEEI, potentially at relatively low cost. Policy makers are attracted to this type of policy for this and other reasons (for example, consider the rapid proliferation of renewable portfolio standards around the world (Langniss and Wiser 2003; Berry 2002; Berry and Jaccard 2001). However, the outcomes of these non-price policies (including both cutting edge policy instruments like renewable portfolio standards and vehicle emissions standards as well as traditional mechanisms like command and control regulations governing the use of specific technologies) can generally not be simulated by top-down models because of their crude representation of technologies. Consequently, it is likely that conventional top-down models will underestimate future values of AEEI and ESUB and consequently predict high costs of compliance with new policies<sup>6</sup>. For a similar reason, top-down models are not useful for understanding the specifics of technology evolution – i.e., they do not predict how specific technologies will evolve under different scenarios.

Bottom-up models, in contrast, tend to systematically underestimate the economic costs of environmental energy policies. Since they do not account for consumer preferences, they overestimate the willingness of market participants to switch to cleaner technologies, which often have a lower financial life-cycle cost than polluting technologies at the social

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<sup>6</sup> It is also possible that future values of AEEI and ESUB could actually be lower than their historic values, leading to an underestimation of the costs of compliance with new policies by top-down models. However, the environmental, social, and political signals in the future will likely all push these parameters lower in the future.

discount rate, but which can have a higher welfare cost due to intangible decision variables like risk and qualitative preferences. Bottom-up models are therefore most useful for highlighting the *potential* for energy efficiency improvements rather than for providing realistic policy simulations, which are often of greater interest to policy makers.

Grubb et al. (1993) 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. 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). Some formerly top-down models have evolved to increase the degree to which they are able to represent technologies by disaggregating demand functions. Some formerly bottom-up models 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 approach, are developing a new generation of models that attempts to borrow from the strengths of both top-down and bottom-up. These new models, called hybrid models, could prove useful to policy makers assessing the relative strengths of climate change mitigation and other policies.

### ***1.3 Hybrid models***

A hybrid model is an energy-economy model that attempts to bridge the methodological schism between bottom-up and top-down modelling 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 modelling, with varying degrees of success.

Hoffman and Jorgenson (1977) developed the earliest documented effort towards a hybrid model. Their model is based on an input-output model of the US industrial and household sectors, which feeds energy price and energy and commodity demand values to a linear programming model of the energy supply sector. The energy supply model then determines the cheapest way of meeting the required energy supply by choosing the 'optimal' technologies. The energy supply model generates an updated price estimate for the different fuels, and these are fed back into the input-output 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 supply model is a linear programming (financial cost optimization) model, Hoffman and Jorgenson's model lacks behavioural realism at this level. Further, only energy supply technologies are modeled in a technologically explicit manner; all other sectors are modeled in the traditional top-down aggregate manner.

More recently, Jacobsen (1998) has attempted a hybrid model for the Danish economy. His model, Hybris, links the Danish macroeconomic model, ADAM, with three linear programming modules representing energy supply, household electricity demand, and household heat demand. ADAM 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 macroeconomic model, while only short-run fuel demand is determined in the linear programming modules. This limits the effectiveness of explicitly representing technologies in the 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 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 modelling 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 portraying technological evolution. In each case, a financial cost optimization model for technological evolution is linked to a macroeconomic characterization of the major economy linkages. But this mixing of different modelling styles is problematic because while an empirically based macroeconomic model might provide reliable estimates of product substitution, financial cost optimization does not provide a reliable estimate for technological evolution. 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 energy supply and demand representation of the model.

The CIMS model of the Canadian energy economy attempts to do this (Jaccard et al. 2003; Nyboer 1997; Jaccard et al. 1996)<sup>7</sup>. CIMS is an explicit technology vintage model, meaning that it tracks the evolution of technology stocks over time through retirements, retrofits, and new purchases<sup>8</sup>. 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 formula<sup>9</sup>:

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

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

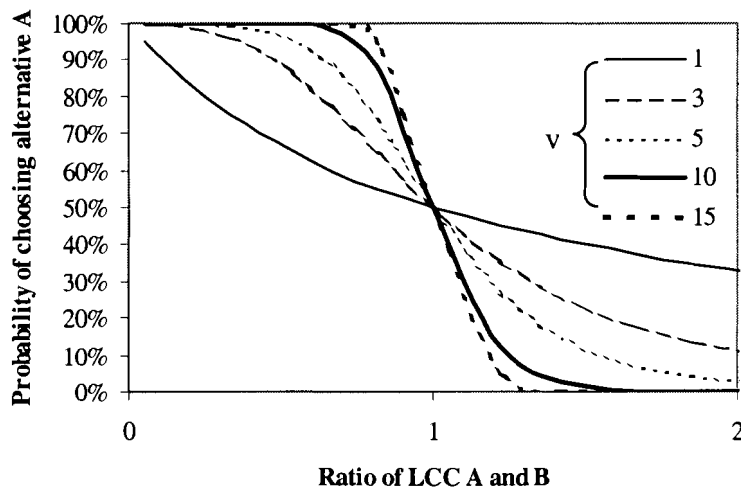
<sup>7</sup> The NEMS hybrid model of the US energy economy, discussed in Chapter 4, is similar in many ways to the CIMS model.

<sup>8</sup> CIMS uses an external forecast to supply information on demand for energy services. Research is currently being conducted to enable CIMS to generate its own macroeconomic forecast through the use of a general equilibrium approach.

<sup>9</sup> 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.



(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 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 2 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 2 - CIMS logistic curve**

The discount rate in CIMS has been estimated through a combination of literature reviews of empirical studies and expert opinion (see Nyboer 1997). The 'v' and 'i' parameters, however, cannot be measured directly. Instead, they are chosen so that the resulting market shares are similar to our expectations and external forecasts. The current process is subject to three shortcomings that cast doubt on CIMS's analysis of various policy options (see Horne and Rivers 2002 for a more thorough discussion)<sup>10</sup>.

<sup>10</sup> It should be stressed that these are shortcomings of the process used to assign parameter values, and they are not necessarily a product of CIMS' algorithms.

1. The behavioural parameters have not been simultaneously estimated from empirical evidence (e.g., by multiple regression), so it is not clear if the current values result in a realistic portrayal of behaviour, especially over a wide range of attribute levels. Even when the parameters are chosen so that CIMS' benchmark predictions match current technology market shares, there is no guarantee that the model will produce valid cost estimates when policies are simulated.
2. Because the parameters have not been empirically estimated in a systematic manner, there is no way of knowing and portraying the uncertainty associated with each parameter.
3. No method exists to directly simulate changes in non-cost attributes of technologies (because they are accounted for in combination using 'v', 'i', and 'r').

To address these shortcomings, EMRG is testing methods to empirically estimate the parameters in CIMS. 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.

#### ***1.4 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 demand<sup>11</sup>. They are based on the postulate that consumers are utility-maximizers: when faced with a particular choice set, consumers choose the option

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<sup>11</sup> For a more complete overview of DCMs, see for example, Ben-Akiva and Lerman (1985), Louviere et al. (2000), or Train (2002).

that brings them the most satisfaction or utility<sup>12</sup>. 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  $\beta_k$ '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  $\beta_j$  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:

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

Where CC is the capital cost of car j, OC is the operating cost, and TT is the travel time, and  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$  are the weighting coefficients estimated from the data that show the importance of the capital cost, operating cost, and travel time, respectively, to the decision outcome. Due to contextual and temporal variation and other non-measurable

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<sup>12</sup> 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*.

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  $\varepsilon_j$  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<sup>13</sup>:

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

Substituting for  $U_i$  and  $U_j$  gives:

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

Equation 6 can only be solved if an error distribution is assumed for  $\varepsilon_i$  and  $\varepsilon_j$ . For analytical tractability, it is usually assumed that  $\varepsilon_i$  and  $\varepsilon_j$  follow Type I Extreme Value distributions<sup>14</sup>, and that  $\varepsilon_i$  and  $\varepsilon_j$  are independent of one another. Under this assumption, integration of Equation 6 gives the multinomial logit function:

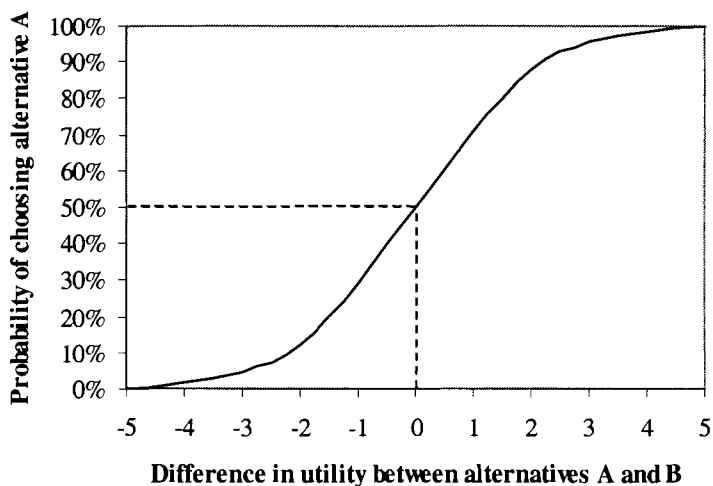
$$\Pr(j | A) = \frac{e^{V_j}}{\sum_{j=1}^J e^{V_j}} \quad (7)$$

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<sup>13</sup> Throughout this paper, “the probability of choosing an alternative” is used synonymously with “the market share of an alternative”.

<sup>14</sup> The Type I Extreme Value distribution, also known as the Gumbel distribution, is an asymmetric, closed-form distribution similar in shape to the Weibull distribution. We have no reason to believe that the errors should actually be distributed according to this type of distribution, and recently, analysts have solved Equation 6 for other types of distributions and for less restrictive assumptions about the independence of the error terms (see Chapter 5).

Figure 3 is a graphical representation of (7) for the simplified situation where only two technologies are available to the consumer. Where both alternatives have equal utility, there is a 50% probability of the consumer choosing each alternative. As the utility of alternative A increases over that of alternative B, the probability of choosing A increases. The shape of the logistic function means that changes in utility have the largest influence when both technologies have similar utilities, and much less influence when one of the technologies is clearly dominant. While it is difficult to graphically present a similar situation for more than two technologies, the mathematics work out identically. Note the similarity between the DCM logistic probability curve in Figure 3 and the CIMS logistic probability curve in Figure 2. This similarity is an important reason why DCMs are well suited for supplying behavioural information to CIMS.

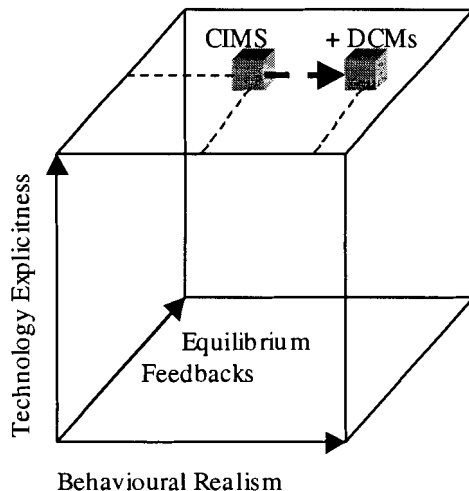


**Figure 3 - DCM logistic curve**

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 modelling provides an analytical framework for quantifying the importance of

various attributes of technologies, and predicting how consumers will respond to changes in those attributes.

Returning to our representation of energy-economy models by their positions along the three axes of technological explicitness, behavioural realism, and macroeconomic feedback, the current CIMS hybrid model is situated toward the right rear corner of the conceptual box in Figure 4 (for comparison refer to Figure 1). It is technologically explicit and has many features of equilibrium feedback, although not as completely as would most CGE models. The model is also behaviourally realistic, although its behavioural parameters are estimated from a combination of review of other empirical studies and expert judgment. The goal with using the information from DCMs is to shift the CIMS hybrid model further along the behavioural realism axis. It needs to be emphasized that the completed model, while having more rigorous empirical basis for its behavioural parameters, cannot be considered fully behaviourally realistic, as it is impossible to predict future behaviour with certainty (this point applies equally to all energy-economy models).



**Figure 4 - Conceptual representation of CIMS and research objective of this project**

*Source: Adapted with permission from Jaccard et al. 2002*

### ***1.5 Integrating the results of DCM research into hybrid 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 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. Also, it would be a monumental task to conduct DCM research into every choice made in the economy between different technologies and processes (such as modes of travel). Moreover, such research would need to be repeated every few years as new technologies appeared. DCM research offers the possibility, however, of providing greater confidence in some of the key parameters for some of the key technology choices in a hybrid model.

Integrating DCM research into CIMS (or other hybrid models) can be accomplished by either replacing the current CIMS algorithm by DCM functions at each technology competition node, or by manipulating the parameters in the CIMS competition algorithm to reflect the results of DCM research. Each method has particular advantages and disadvantages, but both retain the technology specific behavioural realism crucial to an effective hybrid model. These methods are explored more thoroughly in chapter 4.

The parameters in a DCM are empirically estimated from survey or market data, meaning that it is possible to empirically estimate the uncertainty associated with each variable (each  $\beta$  in Equation 3). Since parameters in CIMS are estimated from the utility function of the DCM, it is also possible to estimate uncertainty in these parameters, and in theory to propagate these estimates of uncertainty through to the model results. Such an

undertaking would be extremely useful, because it would avoid promoting a false sense of confidence in modellers and policy makers, and it would allow results from CIMS to be more rigorously compared to results from other models. Without empirical estimates of the parameters in a model, it is extremely difficult to assign justifiable estimates of uncertainty. DCMs allow for justifiable estimates of uncertainty in this form of hybrid model. A further discussion of uncertainty can be found in chapter 4.

Because of the vast number of technologies and processes in the energy sector, producing this type of hybrid model would require a large number of DCMs to be estimated. Analysts have been using DCMs at a single-technology level to predict technology choices for some time. DCMs have been developed to predict personal transportation choices (e.g., Ewing and Sarigollu 2000; Bunch et al. 1993; Calfee 1985), housing choices (e.g., Earnhart 2002; Palmquist 1984), and appliance choices (e.g., Fernandez 2001; Revelt and Train, 1998; Hausman 1979). However, only some of this research is focused on technology choices that affect energy consumption. This subset of research, along with dedicated studies to augment our understanding of factors affecting key technology decisions, could be used to provide an empirical foundation for the behavioural parameters in these sectors of a hybrid model. However, there are still many technology decisions that have not been studied with discrete choice methods. Industrial and commercial technology decisions in particular have not been adequately studied. Given that the industrial and commercial sectors represent over 40% of Canada's energy use, this is a serious research gap (NRCan 2000). This study will therefore focus on energy using technology decisions in Canada's industrial sector.

## ***1.6 Summary and research overview***

While top-down and bottom-up models have been incrementally improving over the past quarter-century, both face fundamental theoretical weaknesses that point towards the need for a paradigm shift in energy-economy modelling. Early forms of hybrid models have arisen in the past twenty years to address this need, yet most of these are simple extensions of top-down and bottom-up models and do not fully remedy the problems with



using the more traditional models. CIMS possesses the desired features of a more complete hybrid model in that its technology representation matches that of detailed bottom-up models, its macro-economic feedback mechanisms are substantial, and its portrayal of technology acquisition and use behaviour is based on market observations. However, while there is some real-world empirical basis for its critical behavioural parameters, they also depend to a significant degree on judgment. Improving the empirical basis for these parameters would increase the model's plausibility and thus usefulness to policy-makers. This research uses discrete choice models to capture consumer preferences at a technology-specific level.

Following this modelling path points towards the requirement for a significant amount of work in estimating DCMs at critical energy service demand nodes. Most of the energy-related DCM work that has been conducted by other analysts focuses on the transportation and residential sectors, with little research conducted on discrete choices in the industrial and commercial sectors, which consume a large amount of energy and may offer some of the best opportunities for energy efficiency improvements.

This research is consequently aimed at furthering our knowledge of industrial decisions that affect energy use by using a discrete choice model. The results of the discrete choice model are then used to inform the behavioural parameters of the CIMS hybrid model<sup>15</sup>.

The industrial sector is extremely diverse, with energy consumption originating from a huge range of technologies and processes that vary from industrial sector to sector. Some technologies, however, are commonly used throughout all of industry. Such technologies are referred to as auxiliary technologies and include pumps, conveyors, motors, fans, and steam generating technologies. Steam generating technologies in particular are responsible for a large amount of total industrial energy use<sup>16</sup>.

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<sup>15</sup> In Chapter 4, I also apply the DCM research in this paper to the NEMS (National Energy Modelling System) hybrid model of the US energy-economy.

<sup>16</sup> The Manufacturing Consumption of Energy Survey (MECS), conducted in the US every three years, has found that 31% of all primary energy in industry is devoted to raising steam in boilers (cited in EIA 2003).

Steam is generated in industry through three basic technologies – standard efficiency boilers, improved efficiency boilers<sup>17</sup>, and cogenerators. Cogenerators essentially couple a boiler with an electrical generator to use the same fuel source to produce both heat and electricity at higher thermodynamic efficiency than stand-alone boiler and electrical generation systems. This technology is discussed in detail in the following chapter. Each of these three technologies has different energy use and emissions fingerprints and different costs. In particular, there is a large difference in energy consumption between boilers and cogenerators, and therefore a large potential for energy and emissions reduction from switching to cogeneration. There are an estimated 4,000 large industrial boilers in Canada today, many of which will need to be replaced or upgraded in the coming decade (Klein 2001). Studying the steam generation technologies in industry is therefore extremely important for our ability to develop a realistic hybrid model in the manner described above.

The remainder of this paper presents a discrete choice study to understand industrial steam generating technology purchase decisions. Chapter 2 briefly describes the technologies and their status in Canada. Chapter 3 describes the methodology followed in conducting the discrete choice survey. Chapter 4 summarizes the results of the discrete choice survey and discusses the implications for policy. This chapter also deals with integrating the industrial steam generation discrete choice model into CIMS – a representative bottom-up based hybrid model. Chapter 5 concludes and includes recommendations for further research and a discussion of the limitations of this research.

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<sup>17</sup> Improved efficiency boilers use vibrating gates, heat recovery systems, and regenerative boilers to increase the efficiency at which steam is generated.

## 2. Steam Generating Technologies

### *2.1 Cogeneration technology and economics*

Virtually all industrial plants require both heat and electricity in order to operate. Conventionally, heat is obtained by burning fossil fuels on site in a boiler to produce steam, and electricity is obtained from the electric grid. Although over 70% of Canada's electricity is hydroelectric or nuclear, in most provinces economic and environmental concerns limit hydroelectric and nuclear capacity, and most new electric generating capacity is thermal (fossil-fuel based)<sup>18</sup>.

Any time electricity is generated from a thermal source (i.e., fossil fuel combustion), waste heat is produced due to inefficiencies in the generation process and inherent thermodynamic constraints that limit the amount of electricity that can be produced from a combustion process. Electrical efficiencies of commercial thermal electricity power plants range from about 35% to 50%, meaning that up to 65% of the available energy in the fuel ends up as heat rather than electricity<sup>19</sup>. In large centralized power plants, there is usually no demand for this amount of heat, so it is typically vented to the atmosphere as a byproduct of the electricity generation process. However, if the electric power plant is situated where there is demand for heat, the waste heat from the electricity generation process can be used to displace demand for heating energy. Making use of the byproduct heat from the electricity generation process is known as cogeneration. Cogeneration essentially uses the same fuel source to produce both electricity and useful heat and in so doing can result in significant reductions in energy consumption (Joskow and Jones 1983). Overall efficiencies of cogeneration systems are typically between about 75% and

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<sup>18</sup> In 1999, the National Electricity Board (NEB) estimated that over 60% of the new electricity generation capacity commissioned until 2025 will be gas-fired capacity. Hydroelectric capacity is projected to make up much of the remaining 40% (NEB 1999).

<sup>19</sup> A small portion of the available energy in the fuel actually remains as unburned hydrocarbons due to poor mixing of fuel and oxygen. This is especially true in coal-fired or biomass-fired power plants, where the solid fuel hinders complete mixing of fuel and air.

85%, representing a large improvement over traditional generation of heat and power (MKJA 2002). Additionally, because the electricity is produced at its point of use, the need for transmission is eliminated, further reducing the cost and improving the efficiency of cogeneration relative to conventional generation.

Cogeneration systems can be sited anywhere that there is a significant demand for heating energy. In industrial applications, heat is required both for processes (e.g., pulp drying, sterilizing, steam reforming) and for space heating or cooling (heat energy can be converted to cooling through the use of absorption chillers). In commercial and residential settings, heat energy can be used to provide space heating or cooling. Cogeneration is widely employed in industry and commercial institutions throughout the world, and in Europe it is also used in district heating systems.

Cogeneration is not a technology in itself, but rather an approach to applying technologies. All cogeneration systems are made up of an electricity generator and a heat recovery system, however within this basic configuration there exists much variety. Cogeneration systems are typically classified in two main ways – first by the type of prime mover that is used to convert thermal energy into mechanical energy for the electricity generator, and second, by the order in which they generate heat and electricity.

Most industrial cogeneration systems use **Steam Turbines** as their prime mover (MKJA 2002). A steam turbine relies on high-pressure steam generated in a steam boiler to turn a turbine as it expands and cools. Because almost any fuel can be used to raise steam in a boiler, steam turbines are the most flexible type of cogeneration systems. Steam turbines range in size from about 500 kW<sub>e</sub> to about 80 MW<sub>e</sub>. Steam turbines generally have a low electrical efficiency and therefore a high heat to power ratio (HPR – the ratio of the amount of heat produced to the amount of power, or electricity, produced).

**Gas Turbines** burn gaseous fuels in a combustion chamber whose high-pressure exhaust gases turn a turbine directly. Gas turbines have become more prevalent in Canada recently, particularly for large installations. They have a high electrical efficiency and

consequently a relatively low HPR (MKJA 2002). In some cases the exhaust gases from a gas turbine are used to produce steam for use in a steam turbine, using a configuration called a **combined cycle gas turbine**, which has even higher electrical efficiency than normal gas turbines. Gas turbines are starting to become available in extremely small sizes called **microturbines**. These microturbines range in size from about 25 kW<sub>e</sub> to about 150 kW<sub>e</sub> and can be attractive to small industrial consumers because of their high modularity and extremely low installation time (Brandon and Snoek 2000).

**Reciprocating Engines** burn liquid or gaseous fuels at very high electrical efficiency. Heat recovery from a reciprocating engine is made difficult however, because much of the waste heat is lost as low quality heat through the engine cooling system.

In addition to varying depending on what type of prime mover is used to power the electricity generator, cogeneration systems can take two basic forms depending on what order heat and electricity are produced and used in. In a **topping-cycle** cogeneration system, heat is produced in a combustion chamber or boiler, and used directly to turn a turbine. Upon exiting the turbine (at lower temperature and pressure), the steam or exhaust gases are captured and used in a heating application. A topping-cycle system places emphasis on the electricity generated from a cogeneration system and uses the heat as a by-product. In a **bottom-cycle** cogeneration system, heat is again produced in a combustion chamber or boiler, however, this heat is used directly in a process requiring high quality heat, such as in the glass or metal processing industries. After its use in the process, the steam is fed through a turbine to generate electricity. Bottom-cycle systems emphasize the steam or heat produced in the cogeneration process, and treat the electricity production as a by-product.

While the economics of industrial cogeneration are strongly influenced by the type of prime mover used, the fuel type, and the order of generation, there are some overriding issues that apply no matter the specifics of the system. First, for a cogeneration system to be economical, it is important that heat is required for a large portion of the year. As a rule of thumb, the European Association for the Promotion of Cogeneration recommends

a heat demand of at least 50 kW for at least 4,500 hours of the year (European Association for the Promotion of Cogeneration 2001). In addition, the heat demand should be fairly uniform, as most large cogeneration systems have relatively slow response times. Second, it is almost always more economically desirable to “match” steam load rather than electricity load. In other words, at any point in time the cogeneration system should only raise enough steam to match the process and space heating demands (Joskow and Jones 1983). The electricity that is generated is used to offset grid purchased electricity, and if produced in excess, can be sold to the electric utility (where possible). Third, because of this potential requirement for financial interaction with the electric utility, the relationship between the cogenerator and the electric utility is crucial to the economical operation of a cogeneration system. In particular, the rate offered by the electric utility for electricity generated by a cogenerator (the buyback rate) is important, as is the rate at which the electric utility offers to sell electricity to the cogenerator (the backup tariff). Fourth, the fact that a cogeneration system results in energy savings over traditional generation is not enough to make it economical. Because cogeneration systems have higher capital costs than standard boilers, the incremental electricity savings from a cogeneration system need to outweigh the incremental capital cost of the cogeneration system (Joskow and Jones 1983, Rose and McDonald 1991).

## ***2.2 Status and potential of cogeneration in Canada***

Cogeneration currently accounts for about 6% of Canada’s total electricity generation capacity, with industry accounting for over 75% of the installed cogeneration capacity in Canada (Klein 2001; MKJA 2002). Relative to other developed countries, this number is low. In the Netherlands, cogeneration accounts for 38% of electricity generation capacity, in Denmark, 50%, and in Finland, 32% (Energy for Sustainable Development, 2001). In the larger markets of the United States and Germany, cogeneration accounts for 8% and 11% of the total electricity generation capacity respectively. The European Union, in recognising the potential for cogeneration improve energy security and efficiency, has called for doubling the amount of cogeneration by 2010, from 9% of total

electricity capacity to 18% (European Commission 1997). This is based at least in part on models that estimate the total techno-economic potential of cogeneration is over 40% of Europe's electricity demand (European Commission 1997). In the US as well, government has called for an increase in cogeneration in the coming decade. A model of the US industrial sector found that industrial cogeneration has the potential to supply 133 GW of electricity in the US by 2020 (Lemar Jr., 2001), almost 40% of the estimated new generating capacity that will be required. In both Europe and the US, governments have enacted policy instruments to support the development of cogeneration.

Analysts in Canada have attempted to estimate this country's technical potential for cogeneration as well. Analysis by MKJA (2002) shows that cogeneration could supply 40 GW<sub>e</sub> by 2010 if it was used in all applications where it makes technical sense (i.e., cogeneration would not be used in single family homes because there is currently no viable cogeneration technology on this small scale)<sup>20</sup>. Analysis by Hagler Bailly Canada (2000) shows that the total technical potential for industrial cogeneration in Ontario is about 15 GW<sub>e</sub> by 2010 (a similar estimate to MKJA if the Ontario potential is scaled up to Canada for GDP and population – a factor of approximately 3). Under business as usual (BAU) forecasts, Canada is predicted to be producing less than 10 GW<sub>e</sub> through cogeneration in 2010 (MKJA 2002), just 25% of the total technical potential estimated in the two studies discussed.

Analysts often refer to the low penetration of apparently cost effective energy efficient technologies as the energy efficiency gap (Jaffe and Stavins 1994). Part of the energy efficiency gap is likely due to real market failures or market distortions that inhibit the optimal penetration of energy efficient technologies (in this case cogeneration)<sup>21</sup>, while part is likely because purchasing a cogeneration system is an irreversible technology

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<sup>20</sup> This represents approximately 30% of the total generation capacity that will be required in 2010 (NEB 1999).

<sup>21</sup> The optimal penetration maximizes social welfare.

investment in an inherently uncertain and risky world. Each of these has different policy implications.

Market failures and market distortions are conditions in the market inhibiting the spread of cogeneration that could merit correction by public policy. They are examples of the market not functioning perfectly and can therefore be thought of as lowering social welfare. Analysts have identified several market failures pertaining to cogeneration<sup>22</sup>. First, actual electricity prices are probably lower than socially optimal (i.e., the electricity rate is lower than the marginal social cost) both because of subsidies and because of the method used to price electricity. In Canada, for example, research on CANDU nuclear reactors is heavily subsidized, financial liability in the case of reactor failure is underwritten by the public, and decommissioning is not fully included in the electricity rate (Hagler Bailly Canada 2000). Electricity prices in Canada are also mostly based on the average cost of supplying electricity, rather than the marginal cost, which would typically be higher<sup>23</sup>. These suppressed electricity prices likely act to lower the penetration of cogeneration.

Second, most provinces in Canada do not allow cogeneration facilities to sell electricity to final customers at retail prices, which are typically higher than the wholesale price offered by the grid<sup>24</sup>. In Alberta, where retail access was granted to cogeneration facilities over two years ago, installations of cogeneration have rapidly increased (MKJA 2002).

Third, in Canada there is a lack of clear standards governing interconnection between a cogeneration facility and the electric grid. In any case where a facility wishes to sell

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<sup>22</sup> This section draws on several papers that have been written about barriers to cogeneration, both in Canada (MKJA 2002; Hagler Bailly Canada 2000; Evans 1993) and more broadly (Lemar Jr. 2001; Soares et al. 2001; Andrepont 2000; Karamanos 1998).

<sup>23</sup> Only in Alberta are electricity prices based on marginal costs. Ontario briefly deregulated its electricity industry in May of 2002, but shortly thereafter fixed retail electricity prices, effectively re-regulating the industry. In all other provinces, electricity prices are based on average costs.

<sup>24</sup> Again, only Alberta and Ontario allow retail electricity grid access by cogeneration facilities. Nova Scotia uses an informal net-metering system for small-scale generators (MKJA 2002).



electricity to the grid, the two parties must enter into regulatory and technical discussions, which can be time consuming and detract from the attractiveness of cogeneration. In contrast, the US has developed clear regulations governing grid interconnection, which reduce uncertainty in this regard (Fox-Penner 1990; Lemar Jr. 2001)<sup>25</sup>.

Fourth, it is probable that there is a lack of information in the market regarding cogeneration technology (as there is about for most technologies)<sup>26</sup>. For a market to function efficiently, information needs to be available to consumers. When it is not, the choices made by consumers can diverge from what would be expected given perfect information. Information will likely be underprovided in the market because of its public good characteristics: once created it can be used by other firms at little or no additional cost (Jaffe and Stavins 1994). Further, because the act of technology adoption by a firm creates a positive externality by providing information to others for which the original firm will not be compensated, there is less incentive for technology investment by firms.

While each of the market failures and market distortions discussed here act to lower social welfare, they do not automatically merit correction by public policy. In fact, only those market failures and market distortions that can be eliminated at a social benefit (i.e., those market failures whose elimination can pass a clear cost/benefit test) should be eliminated. Jaffe and Stavins (1994) acknowledge that this is a vague concept, and that it can be difficult to subject potential policies to a credible *ex ante* cost benefit analysis. Developing these cost benefit analyses can be one role for energy-economy models.

As mentioned earlier, market failures and market distortions are only one of the potential sources of the energy efficiency gap. Rational decision makers operating in a world where prices (in particular energy prices) are uncertain may choose not to make an

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<sup>25</sup> Although all states are required to make standard offers, it is left to the discretion of the individual states to decide the actual form of the contract. Different states have different minimum size limits and can offer contracts either in the form of tariffs or as blank contracts (Fox-Penner 1990).

<sup>26</sup> Chapter 4 of this paper empirically demonstrates the lack of information regarding cogeneration facilities in the market.

irreversible investment in a technology, even when it appears cost-effective at today's energy prices, because a change in (energy) prices could render it cost ineffective. This sort of aversion to risk is by no means irrational decision making and could be the source of what some analysts perceive as "unrealistically high" private discount rates (for example DeCanio and Laitner 1997).

Firms contemplating irreversible investments under uncertainty also face an incentive to postpone the investment and wait for better information before investing. Analysts refer to this as the 'option value' of an investment (Dixit and Pindyck 1994; Hasset and Metcalf 1994). The value of waiting for more information before making a decision typically isn't included in analysis of the technical potential for energy efficiency and can significantly detract from the economic potential for energy efficiency investments. Again, choosing not to invest in an energy efficient technology and instead to wait for improved information is a rational decision making strategy that does not merit correction by public policy.

These concepts are illustrated in Figure 5, which shows that if market failures and market distortions relating to cogeneration could be eliminated, the market share of cogeneration would increase from current levels to its techno-economic potential. It would take the elimination of risks, uncertainty, and option value, however, to reach the technical potential of cogeneration, something that is not necessarily desirable from a societal perspective. As discussed previously in this section, only those market failures and distortions inhibiting the adoption of cogeneration whose elimination can pass a cost benefit test should actually be eliminated. In other words, just because a market failure or market distortion exists does not provide grounds for its elimination. Some further public policy measures would be required to reach a true social optimum however, to internalize environmental externalities in the market (Jaffe and Stavins 1994). Again, the goal of public policy in this regard should only be internalizing externalities where it is possible to do so cost effectively.

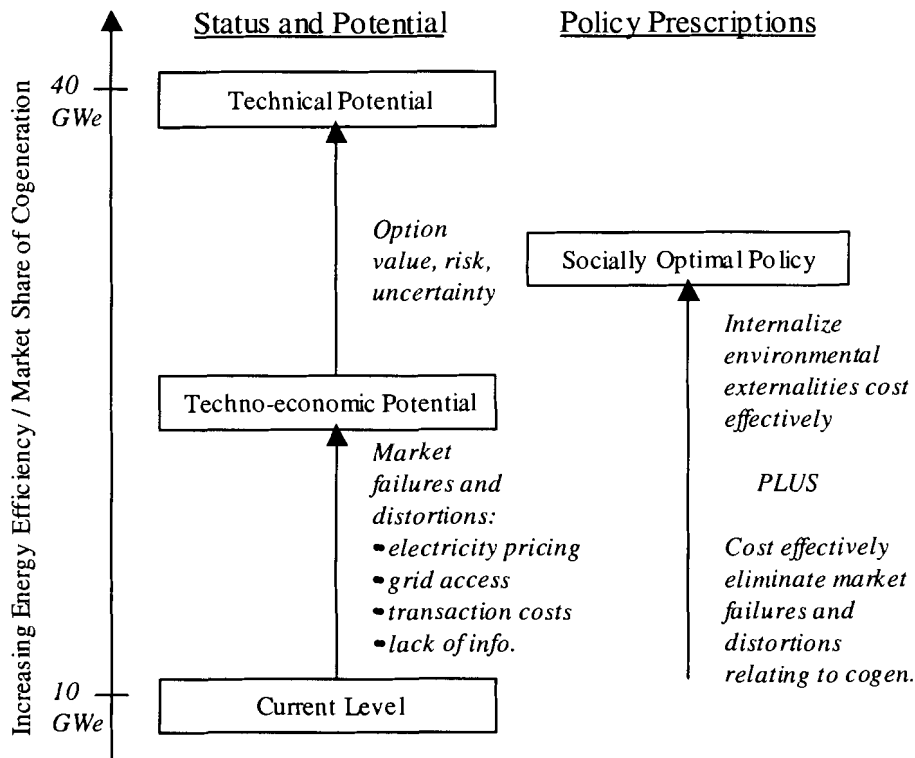


Figure 5 - Cogeneration potential and policies

### 2.3 Cogeneration policies and modelling

Following from the above discussion, public policy to encourage cogeneration can be desirable for two reasons: (i) if it cost effectively reduces market failures or distortions inhibiting the wider adoption of cogeneration, and (ii) if it cost effectively internalizes environmental externalities that result from the limited adoption of cogeneration.

Market failures and distortions limiting cogeneration adoption could be addressed by reducing market transaction costs (opening electric grid access to retail electricity sales by cogeneration facilities and requiring clear standards for cogeneration grid interconnection), by pricing electricity (or at least offering to purchase it) at the marginal social cost of electricity provision rather than the average cost, by reducing subsidies to centralized, non-cogenerated electricity production, and by providing better information to potential producers of cogenerated electricity. Information programs have been used

for more than a decade in Canada and other countries in attempts to increase social welfare through energy efficient technology promotion. There is a vigorous debate about their effectiveness, with analysts finding some programs effective (e.g., the Green Lights program for efficient lighting in the US (DeCanio and Watkins 1998), the CIPEC program for industrial energy conservation in Canada (Westfall et al. 2003; Taylor and Nanduri 2003), the EnerGuide program for appliances in Canada (Nanduri et al. 2002), the Enterprise Energy Audit Program in Australia (Harris et al. 2000), and the Swedish Energy Efficiency Program for industrial and commercial facilities in Sweden (Linden and Carlsson-Kanyama 2002)), and others much less so (e.g., the Voluntary Challenge and Registry in Canada (Takahashi et al. 2001; Bramley 2002)), and the Industrial Energy Extension Service in the US State of Georgia (Sassone and Martucci 1984)). Particularly important to the success of information programs to industry seems to be the provision of detailed plant level recommendations for cost effective energy savings resulting from a subsidized plant energy audit. Such information provision by government can reduce the burden of information search by a private firm and may result in behavioural shift (i.e., change in technology purchase from business as usual).

In addition to attempting to correct for market failures, public policy could be desirable to correct for environmental externalities that reduce the diffusion of cogeneration. Because of the potentially large energy and associated pollution savings available through the wider adoption of cogeneration in industry, energy analysts have for some time advocated public policy to promote cogeneration in the market.

A policy can seek to make cogeneration less expensive or to make low-efficiency alternatives to cogeneration (boilers) more expensive. A capital cost subsidy is an obvious example of the former. Studies of industry decision making generally find that industry requires a two to three year investment payback for energy efficiency investments, implying that the higher capital cost of most energy efficient technologies detracts from their attractiveness (DeCanio and Watkins 1998; Jaffe and Stavins 1994). A subsidy on cogeneration investment (through, for example, a tax credit or accelerated depreciation allowance) would reduce this impediment to adoption. Subsidies can be an

economically inefficient means to achieve a policy end, however, because the greatest benefit of a subsidy program is captured by free riders who needed little or no incentive to invest in the energy efficient technology (Sutherland 2000).

The other mechanism for financially promoting cogeneration is through increasing the relative cost of alternatives to cogeneration. Carbon taxes are currently being proposed in Canada as a policy option for addressing the potential threat of human induced climate change. Because the aggregate CO<sub>2e</sub> emissions of separate generation of heat and electricity are higher than with cogeneration, a tax on CO<sub>2e</sub> would increase the relative cost of traditional generation<sup>27</sup>. This could be expected to increase the diffusion of cogeneration. Because of the short payback (two to three years) required by most industrial firms, however, policies influencing the annual cost of steam generation technologies can be expected to have relatively little effect on the diffusion of cogeneration.

Innovative policy tools called market oriented regulations could potentially help to spur the development of cogeneration in a more cost-effective manner than traditional policy instruments. Market oriented regulations set an aggregate target on a sector of the economy (for example, a market oriented regulation could require that 10% of all new electricity generation was produced through cogeneration facilities). However, although the whole sector is involved in meeting the target, individual actors within the sector are able to choose their level of participation. Some may contribute to the achievement of the target (for example by switching to cogeneration), while some might opt to pay others to do more in order to make up for their non-participation (Jaccard et al. 2002).

In order to predict the cost and effect of these potential policies, analysts and policy makers frequently turn to energy-economy models, which forecast adoption of

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<sup>27</sup> This would be the case in regions where the dominant source of electricity is fossil fuel based. In regions where a large portion of electricity generation is carbon neutral, a tax on CO<sub>2e</sub> could have the effect of increasing the cost of cogeneration relative to traditional generation because of the slightly higher fossil fuel consumption of cogeneration.

cogeneration by industry under different scenarios. The models, however, are typically based either on the erroneous assumption that industrial consumers are financial cost minimizers and always choose the lowest cost technology to meet their needs (e.g., traditional bottom up models), or based on behavioural parameters (e.g., discount rate, technology preferences) that have only been partially empirically estimated from real market data (e.g., the current CIMS model, the NEMS model). Either model formulation may lead to inaccurate predictions of the adoption of cogeneration by industry, and consequently to ineffective public policy.

To remedy this problem, effort needs to be invested in more thoroughly understanding industrial cogeneration decision-making. One method that shows promise for illuminating this decision-making process is discrete choice modelling. A well-structured discrete choice survey could identify and estimate the importance of various cost and non-cost attributes affecting the adoption of cogeneration in industry. However, because investments in cogeneration do not take place in a void, such analysis may be inaccurate if the resulting model does not account for feedbacks from the rest of the economy. As discussed earlier, a solution is to integrate discrete choice model information into a hybrid model to produce a behaviourally realistic, technologically explicit, fully integrated, hybrid model. Using these empirically-derived parameters in an integrated hybrid model to inform cogeneration public policy could lead to more believable modelling results and more effective public policy.

### **3. Survey Methodology**

#### ***3.1 Overview***

The objective of this research is to enable a better understanding of the decision-making process underlying the purchase of steam generating equipment in industry and to use this understanding in an integrated energy-economy model to explore how government policy can influence the evolution of industrial steam generating technology. The approach taken to form this understanding involves gathering empirical evidence regarding equipment purchase decisions in industry and analyzing the evidence using discrete choice modelling techniques.

Estimating a discrete choice model requires a data set composed of many data points, each representing a consumer decision. Each data point consists of the choice set available to the consumer (i.e., each alternative that could have been chosen), the attributes of each alternative in the choice set, and a record of the actual choice that was made by a consumer.

There are two main methods for collecting this sort of data about the behaviour of a population – stated preference (SP) methods and revealed preference (RP) methods. Revealed preference data come from observations of people’s actual choices and behaviour in real-world situations. Stated preference data come from hypothetical or survey situations in which respondents state what their choices would be in the hypothetical situation. Both types of data collection are subject to weaknesses, and it is important to choose the appropriate method for the task.

In particular, the explanatory variables in RP data are often highly collinear and exhibit little variability in the marketplace, which can make estimating a model based on RP data difficult. In addition, RP data have limited value in analyzing the impact of policies that move the economic system beyond its historic boundaries. Finally, RP data are often difficult to gather due to problems with respondent recollection of purchases and

decisions made years in the past. SP experiments are designed by the analyst and so are not constrained by issues of multicollinearity<sup>28</sup> or non-variability of data, and set their own boundaries on economic conditions. Using SP data also allows the analyst to determine preferences for products of which the consumer has little knowledge, for example products new to the marketplace, or products that the consumer did not consider, something that RP data cannot do by definition. SP data, meanwhile, are often biased because when answering a survey, consumers do not face the same constraints present in the real world (budgetary or information constraints). Further biases may arise if consumers do not understand the SP survey properly or if they purposefully bias their answers to alter the survey results. RP data are not subject to these types of problems (Louviere et al., 2000; Train, 2002).

Recently, analysts have attempted to combine RP and SP data to take advantage of the strengths of each while overcoming their weaknesses (see for example Hensher and Louviere, 1999; Train, 2002). Combining SP and RP data was considered for this research, but ultimately not used due to problems obtaining the necessary RP data, and because such methods are in their infancy and the purpose of this research was not to push the frontiers of discrete choice modelling, but rather to gain useful insights about industrial decision making. This research is consequently based on SP data.

To gather the necessary SP data, a choice experiment was administered by mail survey. One of the obvious and primary goals of an analyst conducting a survey is to maximize the response rate of the population being surveyed. In the past 20 years, as telephone costs have dramatically fallen, survey response rates have greatly increased. It is now common for well-designed and well-executed surveys of the general population to achieve response rates of 70% or higher (Paxson et al., 1995). However, several problems unique to business surveys generally result in much lower response rates for this type of survey. In particular, Paxson et al. point to the following problems:

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<sup>28</sup> Multicollinearity occurs when two or more dependent variables move in tandem throughout the period in which data was gathered. This effect makes it difficult to isolate the impact of either of the dependent variables on the independent variable.



- ❑ Businesses are often hard to define. Sending a questionnaire to a business is no guarantee that the appropriate person will receive it.
- ❑ Businesses often have gatekeepers who decide if the survey should reach the respondent.
- ❑ Some businesses have policies that do not allow employees to respond to surveys.
- ❑ The questions asked are often difficult to answer.
- ❑ Financial incentives are usually not appropriate because it is unclear who gets them, and can be unethical for an employee to keep them.

As a partial remedy against this type of problem, Paxson et al. (1995) and Dillman (2000) suggest several techniques that can raise response rates in business surveys. Table 1 details their suggestions and the actions that were taken in this survey response to accommodate the suggestions.

**Table 1 - Suggestions and actions for maximizing survey response**

<b>Suggestion</b>	<b>Action</b>
Conduct a mixed-mode survey	Recruitment and screening using telephone survey; mail questionnaire follow-up
Address survey to appropriate person	Full names were obtained for subsequent mailouts during telephone interview process
Make repeated contacts with respondents	Four contacts were made with respondents: one by telephone and three by mail
Use the most up to date list of businesses possible	Scott's Canadian Manufacturing Directory for 2002 (most recent available) was used to obtain business information
Ask questions that one person in the company can respond to	Questions were constrained to deal with energy issues and deliberately avoided detailed financial issues
Minimize complexity, length, and instructions	Both the telephone and mail surveys were kept short (about 3 and 8 minutes respectively) and questions were kept deliberately simple
"Profile" firms to understand structure and nature of topic	Extensive interviews were conducted with the plant manager of a petroleum refinery and a cogeneration consultant

Following Paxson et al. and Dillman's first recommendation, this survey was based on a mixed-mode survey, with the first contact made through telephone. In this phase, the plant manager was asked whether he/she was willing to participate in the study. If so, several questions were asked regarding energy use in the plant. During the second phase of the study, participating firms were sent a mail survey that included the choice experiment tailored to the characteristics of the firm gathered in the telephone survey<sup>29</sup>. Dillman empirically justifies the use of mixed-mode surveys through their consistently higher response rates and higher quality data than single-mode surveys. This chapter outlines in detail the telephone and mail survey processes.

Simon Fraser University requires that any research involving human subjects undergo an ethical screening process. In this study, all survey respondents were informed that participation in the study was voluntary and that they were free to withdraw from the survey process at any time. Further, all individual firm data collected in the survey was kept confidential and results are only presented in aggregate so individuals cannot be identified. The research was consequently assessed as low risk and granted ethical approval by the University's Office of Research Ethics. The letter granting this project ethical approval is included as Appendix 1.

### ***3.2 Telephone survey***

Although the telephone survey was not used to collect the primary data in the survey, it served three important purposes. First, it was used to identify firms willing to participate in the mail survey. Second, it was used to screen out firms not qualified to participate (in this study, a non-qualifying firm was one that had no potential for conventional cogeneration). Using the telephone survey to screen out non-qualifying and unwilling firms from the mail survey should result in better quality data and an overall lower cost

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<sup>29</sup> Both the telephone survey and subsequent mail survey were translated into French and administered in French where appropriate.

over the alternative of simply using a mass mailing of surveys. Finally, the telephone survey was used to gather some preliminary data on participating firms, which could then be used to customize the mail survey to each individual respondent.

For this experiment, the population of interest was Canadian manufacturing firms with technical potential for cogeneration. Cogeneration is technically possible for a firm with demands for both heat and electricity. Traditionally, cogeneration has been most prevalent in large firms with significant and simultaneous demands for heat and electricity<sup>30</sup>, however, with recent and ongoing developments in micro-turbine technology (see Brandon and Snoek, 2000), and the international trend towards independent power production in the electricity industry, cogeneration is becoming more attractive to small firms with discontinuous demands for heat and electricity (see, for example, Strachan and Dowlatabadi 2002). Cogeneration could be made even more attractive to small firms with dedicated policies to encourage energy conservation or greenhouse gas reduction. Consequently, both small and large firms with demands for heat and electricity were included.

The sample was selected from a database containing firms in all manufacturing sectors in the Canadian economy with at least 20 employees – *Scott's Directory of Canadian Manufacturers, 20+ Employees* (2002). Although a technical potential for cogeneration exists in many industrial sectors, some sectors were excluded from the sample because their heat demand was considered too low to make cogeneration a viable option<sup>31</sup>. After

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<sup>30</sup> Three particularly energy intensive sectors – petroleum refining, chemical production, and pulp and paper production – produce over 75% of the cogenerated electricity in Canada (MKJA 2002).

<sup>31</sup> Industrial sectors were selected based on literature review, a database of current cogeneration facilities in Canada (CIEEDAC 2002), and consultation with John Nyboer, executive director of CIEEDAC. Generally, they were chosen to include those sectors with demand for both heat (in the form of steam) and electricity. Cement, glass, and ceramic manufacturers, who use significant amounts of heat and electricity, were excluded from the sample because the heat used in their processes is generally not steam but dry combustion heat. These industries are modeled differently in CIMS.

this initial screening, 9083 firms were left to make up the sample. Table 2 is a list of the sectors included by 2-digit SIC code<sup>32</sup>.

**Table 2 - Industrial sectors included in sample by 2-digit SIC code**

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

Coverage error in a survey can occur when a sample is drawn from an incomplete subpopulation and the results are subsequently extended to the population as a whole (Dillman 2000). A common example of coverage error occurs when sampling is performed using telephone listings, thereby excluding unlisted numbers (which frequently contain a high proportion of doctors). The key to avoiding coverage error is therefore to obtain a sampling list that is up to date, complete, and accurate. This study used *Scott's Directories of Canadian Manufacturers, 20+ Employees* (2002), which is the most complete and current listing of manufacturing facilities available in Canada (published in February 2002). Although it is inevitable that some facilities on the list have closed, and others not on the list have opened, coverage error for this experiment can be considered

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<sup>32</sup> In many cases, the entire 2-digit SIC sector was not included in the sample. For example, in SIC 38, firms in the medical equipment sector were included (steam could be required for sterilization), while firms in the watches and clocks sector were not. This survey used the 1987 US SIC classification system. This system is not equivalent to the Canadian SIC system.

low. To avoid coverage error, the results of this research should only be considered applicable to the industrial sectors included in the survey, and for companies with at least 20 employees.

McIntyre and Mustel Research Ltd. (MMRL), a Vancouver-based market research firm, was retained to conduct the telephone interviews. MMRL randomly selected 8541 firms from the 9083 on the sample list for inclusion in the telephone survey. Between October 9 and 27, 2002, MMRL contacted firms from the sampled list in order to select firms qualified to and willing to participate in the study. Firms were considered qualified to participate in the study if they currently used steam for process or space heating in their plants. 592 firms (6.9% of the firms called) met these criteria and were willing to participate in the study. Almost 40% of the firms called did not qualify for the survey, meaning that steam is not currently used in their plants. This is surprisingly high, since the survey was administered to sectors that are known users of steam. Such a high rate suggests that there might have been some problem interpreting the question. The refusal rate of about 10% in the survey is low for a “cold-call” survey of industry. A full call summary report for the telephone survey is presented in Table 3.

**Table 3 - Call incidence report**

<b>Number</b>	<b>Percent</b>	<b>Outcome</b>
592	6.9%	Completed
3129	36.6%	Non-Qualifier
1007	11.8%	Busy/No Answer/Not in Service/Wrong Number
1968	23.0%	Appointment Made
903	10.6%	Refusal
942	11.0%	Other
8541	100.0%	Total

Firms that qualified for the survey and indicated their willingness to participate were subsequently asked several questions regarding energy use in their plants. All questions asked in the telephone survey were categorized “closed-ended” questions to encourage accurate response to questions which otherwise would be challenging to answer by telephone. The primary goal of the telephone interview was to gather data regarding what

type and size of steam production system (i.e., fuel type, steam capacity, and steam pressure) was in use by the firms in the study. Appendix 2 includes the full script of the telephone survey used.

The telephone survey was targeted at the plant manager of the firm, who was judged to be the individual most likely able to provide meaningful and accurate answers to the questions asked. Because the Scott's Directories Database provides telephone numbers for main switchboards of companies, MMRL required a two stage telephone survey process, where initial contact was made with the receptionist at the switchboard to obtain the name and telephone number of the plant manager in the first stage, and the plant manager was contacted separately for the telephone interview in the second stage. This two-stage process likely reduced the percentage of successful call attempts in the survey over a more direct one-stage telephone survey.

### ***3.3 Mail survey***

#### **Mail survey design**

The mail survey questionnaire was composed of two main parts. In the first part, respondents were asked qualitative questions about decision-making in the company, awareness of cogeneration, perceptions about cogeneration, and attitudes towards different types of policy instruments. While the focus of this survey was on the discrete choice experiment, qualitative questions were included in the survey because they provide context for analyzing the discrete choice experiment and a richer understanding of the preferences and behaviour of the firms in the sample. A sample survey is included in Appendix 3 and shows the full transcript of the qualitative questions asked in the mail survey.

The second part of the survey was the discrete choice experiment. In a stated preference choice experiment, participants are presented with hypothetical choice situations from which they must choose the option that best satisfies their needs. For this experiment,

which sought to quantitatively analyze the importance of factors influencing the decision of which type of industrial steam generating equipment to purchase, plant managers were asked to assume that their primary plant boiler needed replacement. In the experiment, three technologies were available for purchase by the plant manager – a standard efficiency boiler (SEB), a high efficiency boiler (HEB), and a cogeneration system (COG). These choices roughly reflect the breakdown of the industrial steam generation node in CIMS. However, CIMS also allows industries to choose the type of fuel that best suits their needs. In this survey, the question of fuel choice was not addressed because it would have rendered the choice experiment intractable<sup>33</sup>. Instead, respondents were assumed to be constrained to choosing equipment that used the same type of fuel currently used for most of the plant's heating needs. A question in the qualitative part of the survey sought to understand respondent's willingness to switch fuels. Response to this question indicates that firms are relatively unlikely to switch fuels, so the choice question as designed should capture the actual process reasonably well.

Discrete choice modelling is based on the theory that consumers view options in a choice set as 'bundles of attributes' (Meyer and Kahn 1993; McFadden 1974). To choose the most satisfactory option from a group of choices, people implicitly combine the attributes of each choice together to arrive at an overall measure of utility for each option. The option with the highest utility is then chosen (see chapter 1 for a more complete explanation of the theory of discrete choice modelling). When designing a choice experiment, it is therefore crucial to understand which attributes are important determinants of choice outcomes. To this end, interviews were conducted with three professionals familiar with cogeneration in industry<sup>34</sup>. The interviews identified seven

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<sup>33</sup> To test for preferences for four fuel types (for example oil, natural gas, coal, and hog fuel) would have required a choice set with 12 choices (four fuel types and three equipment types). Such a large choice set is too large to be analyzed by the respondent (due to cognitive limits), and would have required a larger sample than was available (due to increased data requirements for estimation). In reality, seven types of fuels were used by the respondents to the survey, which would have required a choice set with 21 options.

<sup>34</sup> Rob Lazenby, facilities manager at Chevron's Burnaby refinery; Paul Willis, energy consultant at Willis Energy Services Ltd.; and John Nyboer, executive director of the Canadian Industrial Energy End-Use Data and Analysis Centre (CIEEDAC).

attributes that have a direct impact on the choice of steam generating equipment in industry, which are shown in Table 4. All interviewees emphasized that the choice of steam generating equipment in industry is strongly determined by site-specific factors. For example, while the footprint of a steam generating system might be a large concern for an urban facility with limited and costly floor space, it might be a negligible concern for a rural facility.

**Table 4 - Attributes considered for inclusion in the discrete choice experiment**

<b>Attribute</b>	<b>Comment</b>
Capital Cost	
Operating and Maintenance Cost	
Fuel/Electricity Costs	Dictated by efficiency and fuel/electricity prices
Construction Time	Amount of time regular plant processes need to be disturbed to install the system
Reliability	Electrical reliability – gains in reliability due to self generation; Overall reliability – difference in failure between boiler and cogenerator
Footprint	Space required on plant floor
Regulations	Difference in permitting between boiler and cogeneration system

The objective of this survey was to understand how government policies could affect the market shares of industrial steam generating equipment. Consequently, only attributes that can be directly influenced by government policy were included in the choice experiment (construction time, reliability and footprint were therefore all excluded). Further, the regulations attribute was excluded since it was unclear that cogeneration systems and boilers required significantly different approvals for construction and it was determined that inclusion of this attribute would add extra complexity to the survey. This left capital cost, operating cost, and fuel and electricity costs as the attributes included in the experiment. Although these are the only attributes explicitly included in the experiment, it was made clear in the survey that respondents should make equipment choices based on actual constraints in their plant (for example space) that might not be explicitly included in the survey. Choices affected by non-included variables such as this are picked up by the alternative specific constant for each technology. It should be made



clear, however, that a more complete utility function could be expected to better capture the rationale underlying consumer decisions. In designing a choice experiment, the analyst makes a tradeoff between the cognitive tractability of the experiment and the completeness of the utility function. In retrospect, this study might have erred on the side of including too few attributes, especially the non-financial cost attributes that are frequently ignored in this type of study. However, much of the literature on industrial decision-making believes that industry is primarily concerned with financial costs in technology choice and not as interested in intangible costs like comfort and status that do not translate directly to the financial bottom line<sup>35</sup>.

Using these attributes for the discrete choice model leads to a utility function for technology  $i$  of the form:

$$U_i = \beta_1 CC + \beta_2 OC + \beta_3 FC + \beta_4 ES + \beta_i + \varepsilon_i \quad (8)$$

Where  $\beta_1$  is the capital cost coefficient,  $\beta_2$  is the operating cost coefficient,  $\beta_3$  is the fuel cost coefficient, and  $\beta_4$  is the electricity savings coefficient.  $B_i$  is the alternative specific constant for technology  $i$  and  $\varepsilon_i$  is the error term for technology  $i$ , which is distributed Type I extreme value and independent from the error terms for all other technologies. The index  $i$  represents each of the three technologies being modeled – the standard efficiency boiler, high efficiency boiler, and cogeneration system. The objective of the discrete choice experiment is to determine the values for each  $\beta$  in the utility function.

A stated preference choice experiment is designed by creating hypothetical choice sets from which the respondent must select the most optimal choice. Each choice set consists of a description of each alternative in the choice set, based on the attributes described above. A sample choice set, as it appeared in the mail survey, is shown in Figure 6.

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<sup>35</sup> However, some intangible costs like risk and the burden of information gathering do translate directly to the bottom line and consequently are considered by industrial decision makers.

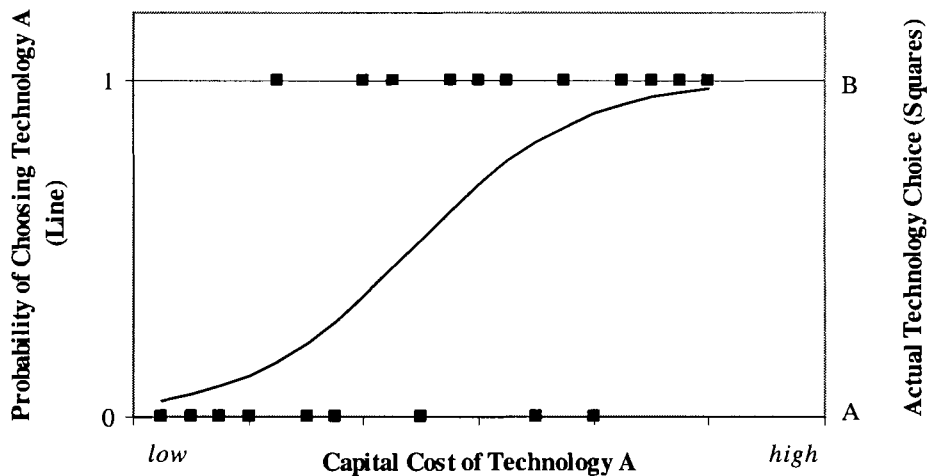
Apart from the attributes discussed above, some other information was provided in the surveys to make them more representative of reality and comprehensible. First, thermal and electrical efficiency values were included to help the respondent distinguish between alternatives. Second, in addition to presenting the actual values of the various cost attributes, the survey presented a simple financial analysis to the respondent, consisting of an NPV curve and a payback period. This information was included to make the survey a closer approximation to the actual decision making process in industry, where decision makers would likely have access to detailed financial analysis prior to making the decision. Harris et al. (2000) report that eighty percent of the firms they surveyed used payback period analysis to evaluate energy efficiency investments and about one third use NPV analysis. Sassone and Martucci (1984) performed a similar survey in the US State of Georgia and report that only 21% of the firms they surveyed used any analytic technique for evaluation of energy efficiency investments. Despite these disparate findings, it was decided that the survey would include both a payback period and NPV analysis. Providing financial analysis on the survey in the case where it would not be used in the firm being surveyed could influence the survey results.

<b>Question 11. If you needed to replace one of the primary boilers at your plant and these were the only three options available, you/your firm would choose (tick one):</b>		
<b>Option 1: Natural Gas Standard Efficiency Boiler</b>	<b>Option 2: Natural Gas High Efficiency Boiler</b>	<b>Option 3: Natural Gas Cogeneration System</b>
<b>Capital Cost</b> \$2,483,000 <b>Operating Cost</b> \$99,000 / yr <b>Thermal Efficiency</b> 76% <b>Electrical Efficiency</b> 0% <b>Total Fuel Costs</b> \$2,035,000 / yr <b>Total Electricity Savings</b> \$0 / yr	<b>Capital Cost</b> \$3,165,000 <b>Operating Cost</b> \$108,000 / yr <b>Thermal Efficiency</b> 84% <b>Electrical Efficiency</b> 0% <b>Total Fuel Costs</b> \$1,651,000 / yr <b>Total Electricity Savings</b> \$0 / yr	<b>Capital Cost</b> \$4,710,000 <b>Operating Cost</b> \$188,000 / yr <b>Thermal Efficiency</b> 77% <b>Electrical Efficiency</b> 8% <b>Total Fuel Costs</b> \$1,883,000 / yr <b>Total Electricity Savings</b> \$614,000 / yr
<b>Base Case</b>	<b>Payback Period</b> 1.8 yr	<b>Payback Period</b> 3.3 yr
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

**Figure 6 - Sample discrete choice experiment**

To estimate the importance of each technology attribute to the choice outcome, choices must be observed at varying attribute levels. For example, to determine how changes in the capital cost of a technology influence the probability of that technology being selected, it is necessary to observe how the choices made by respondents change as the

capital cost of the technology changes. Figure 7 graphically illustrates this process for the simple case where there are only two technologies available to the respondent, A and B. When the capital cost of technology A is low, that technology is chosen by nearly all respondents (each choice is represented by a square)<sup>36</sup>. As the capital cost of technology A increases, some respondents begin to choose technology B. Finally, as the capital cost of A gets very high, almost all respondents choose technology B over technology A. The logistic curve in Figure 7 that best maps the choices is characterized by a shape parameter. This shape parameter is equivalent to the capital cost parameter in the utility function. To estimate the value of each  $\beta$  in the utility function then, hypothetical choice situations are presented to respondents in which each attribute varies and choice outcomes are subsequently observed. The shape parameter, or  $\beta$ , is then estimated for each attribute.



**Figure 7 - Estimation of parameter values from data**

For this experiment, four levels of capital cost were used, two levels of operating cost, four levels of fuel cost, and two levels of electrical savings (for cogeneration systems

<sup>36</sup> In this illustration, the capital cost of technology B is assumed to remain constant throughout.

only)<sup>37</sup>. Each level is simply a multiplier for the appropriate base cost (the method used for determining the appropriate base cost is discussed below). The actual levels chosen are shown in Table 5. In choosing the levels to use, it was assumed that any policy that would affect the relative attractiveness of the technologies would seek to encourage the purchase of high efficiency technologies over low efficiency technologies (cogeneration over high efficiency boiler and high efficiency boiler over standard efficiency boiler).

**Table 5 - Attribute levels for the discrete choice experiment**

Attribute	Technology	Levels			
		1	2	3	4
Capital Cost	SEB	100%	108%	115%	123%
	HEB	85%	98%	112%	125%
	COG	85%	90%	95%	100%
Operating Cost	SEB	100%	115%		
	HEB	85%	115%		
	COG	85%	100%		
Fuel Cost	SEB	100%	108%	115%	123%
	HEB	85%	93%	102%	110%
	COG	85%	95%	105%	115%
Electricity Savings	COG	100%	120%		

Determining how to combine the levels of each attribute to present in the choice experiment is the focus of a vast literature spanning many disciplines called *experimental design*. The design of this experiment was based on overviews of experimental design literature found in Montgomery (1991), Louviere et al. (2000), and NIST/SEMATECH (2002).

<sup>37</sup> More levels were used for the capital and fuel cost attributes than the operating cost attribute because these costs dominate the total cost of the heating equipment.

With an infinite budget and infinite amount of time to conduct the experiment, a *full factorial design* would have been used for the discrete choice experiment. In a full factorial design, every level of every attribute is combined with every level of every other attribute and multiple data points are observed at each combination. With six four-level attributes (SEB, HEB, and COG capital cost, and SEB, HEB and COG fuel cost) and four two-level attributes (SEB HEB and COG operating cost and COG electrical savings), obtaining six data points at each combination (Louviere et al. (2000) recommend obtaining 6 data points at each observation as a rule of thumb) would require  $6 \times 4^6 \times 2^4 = 393,216$  data points (this design is called a  $2^{16}$  full factorial). Assuming that each respondent to the survey answers four choice situations, this would require almost 100,000 respondents to the survey. Collection of such a large sample is clearly far beyond the means of this experiment. Further, as discussed earlier in this chapter, there are only about 9,000 firms in the sample, which further constrains what is possible in terms of data quantity.

This being the case, it was not possible to use a full factorial experimental design (such a design is not used in most experiments for similar reasons). Collecting less data points obviously means that the analysis will not be as rich, but careful selection of the appropriate data points minimizes the loss of information in the analysis. Choosing the appropriate data points is accomplished using a *fractional factorial design*. Fractional factorial designs are used when the researcher is more interested in the main effects of the attributes than the higher order effects<sup>38</sup>. Fractional factorial designs are used because they maintain the *orthogonality* of the full factorial design. A design is considered orthogonal if the effects of any factor balance out with the effects of any other factor. Design orthogonality is crucial to avoiding problems of multicollinearity and is one of the most advantageous features of stated choice experiments.

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<sup>38</sup> A main effect is the direct effect of an attribute on the outcome; for example the effect that changing the capital cost of a cogeneration system has on the likelihood of a respondent choosing that option *ceteris paribus*. A higher order effect is the interacting effect of one attribute combined with another on the outcome; for example the effect that changing the capital cost of a cogeneration system and the operating cost of a standard efficiency boiler simultaneously has on the likelihood of a respondent choosing a cogeneration system *ceteris paribus* (this would be a second-order effect because it looks at the combination of two effects).

Taking the  $1/2048^{\text{th}}$  fraction of the  $2^{16}$  full factorial, a fractional factorial with 32 runs is obtained. 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 a 1% error into main effects estimates as a rule of thumb. The fractional factorial in randomized order is given in the table in Appendix 3. Each row of the table represents a choice experiment. In row 5 for example, the respondent would be asked to make a choice between a standard efficiency boiler whose capital cost was 1.15 times the base capital cost (determined earlier from the telephone survey responses), whose operating and maintenance cost was 1.15 times the base operating and maintenance cost, and whose fuel cost was 1.0 times the base fuel cost; a high efficiency boiler whose capital cost was 0.85 times the base capital cost for a high efficiency boiler, whose operating and maintenance cost was 0.85 times the base operating cost, and so on.

Each respondent was presented with four such experiments, systematically selected from the random set of 32 runs in the table in Appendix 3. Stated choice experiments often present respondents with up to eight different choices, and Louviere et al. (2000) state that neither response quality nor response rate suffers noticeably when respondents are presented with as many as 16 choice experiments each. However, this study used only four experiments in order to keep the entire questionnaire as brief as possible to encourage high response rate and high quality answers. Appendix 4 contains a full questionnaire, including a sample set of four choice experiments. Each choice experiment includes not only figures for the different costs of each technology, but also a payback period and NPV analysis. These were included to more realistically simulate the information that would be available to plant managers choosing large industrial equipment.

The previous discussion refers to the base attribute levels for each technology. These are the levels of each attribute prior to multiplication by the factors in the experimental design and are given in Table 5 and Appendix 3. Because of the enormous range of firm

size and type in the survey, it was not possible to select one universal base level for each attribute. Rather, it was necessary to customize the choice experiment to each respondent. Failure to do so would result in situations where firms were asked to make unrealistic tradeoffs (for example, the situation where a small firm is asked to choose between a multimillion dollar boiler and a multimillion dollar cogeneration system, when it is more used to dealing in the tens of thousands of dollars). To customize the choice experiment, each firm’s steam demand (pressure and output requirements) was determined from the telephone interviews.

The base levels for each attribute were then obtained from the CIMS technology database, which contains information on capital cost, operating and maintenance costs, and thermal and electrical efficiency for standard efficiency boilers, high efficiency boilers, and cogeneration systems of different sizes and using various types of fuel. As in the CIMS technology database, all cogeneration systems were assumed to be bottom-cycle steam turbine cogeneration systems (see chapter 2). Base attribute levels for each system are given in appendix 5. Linear extrapolation was used to determine base costs for a system of any size, given costs from CIMS for 12 and 100 MW<sub>th</sub> sizes<sup>39</sup>. For example, the base capital cost of a 45 MW<sub>th</sub> high efficiency natural gas boiler is:

$$CC_{45\text{ MW } 900\text{ psi Nat Gas HEB}} = \frac{\$(15,750,000 - 4,345,500)}{(100 - 12)MW} \cdot (45MW) + \$2,790,341 \quad (9)$$

Where \$2,790,341 is the y-axis intercept of the line connecting the points (12MW, \$4,345,000) and (100MW, \$15,650,000). Base operating and maintenance costs were calculated in the same manner. Efficiencies were assumed to remain constant throughout the size ranges (as in the CIMS database). Fuel and electricity costs for each steam generating technology were calculated based on the their thermal and provincial electrical

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<sup>39</sup> The subscript “th” refers to the thermal energy production, so 100 MW<sub>th</sub> means 100 megawatts of heat or steam.



efficiency and fuel and electricity prices found in the CIMS fuel price database. In this experiment, as in the CIMS model, all electricity produced by a cogeneration system was assumed to be consumed on site, and therefore to displace electricity that would have been purchased at prevailing industrial electricity rates. In addition, all steam produced by a cogeneration facility was assumed to be consumed on site, eliminating the possibility of merchant cogeneration. Although such transfers of heat and electricity between firms are possible, and are one area where significant growth in cogeneration adoption could be stimulated, this experiment made the assumption that such transfers did not occur. Currently in Canada, plants sharing the heat production from cogeneration facilities are fairly rare.

### **Mail survey administration**

Questionnaires were mailed to plant managers in all firms who qualified for and were willing to participate in the study within one week of completion of the telephone survey. The cover letter accompanying the first survey mailout is included in Appendix 6. Follow-up postcards were mailed to all respondents one week later reminding them to complete the survey and thanking them for completing the survey if it had already been done. A postcard is included in Appendix 6. Three weeks after the postcards were mailed, a final reminder package was mailed to all participants who had not yet returned their surveys. The cover letter that accompanied the final survey mailout is included in Appendix 6. The process described above draws from Dillman (2000), who emphasizes the importance of a mixed-mode survey as well as the importance of repeated contacts for maximizing response rate.

The mail survey received a response rate of 43.8%<sup>40</sup>. This can be considered high for a survey of business. 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

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<sup>40</sup> 21 of the mailed surveys had incorrect addresses, obviously making it impossible for plant managers to reply. The adjusted response rate, taking the incorrect addresses into account, is 45.4%.

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).

In his discussion of survey errors, Dillman (2000) discusses sampling error, which is a natural consequence of extending results from a sample to the population as a whole. Sampling error decreases as the sample size approaches the population size, according to Equation 10 (modified from Ben-Akiva and Lerman, 1985):

$$B = c \sqrt{\frac{(N_p - N_s)(p)(1-p)}{(N_s)(N_p - 1)}} \quad (10)$$

Where B is the sampling error, c is the z-stat (from normal distribution),  $N_p$  is the population size,  $N_s$  is the sample size, and p is the proportion of the population answering each question a certain way<sup>41</sup>.

259 respondents completed the mail questionnaire ( $N_s$ ) from a total population size of 9083 firms ( $N_p$ ) that matched the selection criteria. For a question where  $p = 0.75$ , the sampling error in the survey would be (at a 90% confidence level)  $\pm 4.3\%$  (in other words, 9 times out of 10, p would be between 0.707 and 0.793). An effort was made to maximize  $N_s$ , but budgetary constraints prevented obtaining a larger sample.

### ***4.3 Survey biases and errors***

This survey started out drawing from an initial population of 9083 firms. From that population, 8541 were randomly selected for inclusion in the telephone survey. The telephone survey then identified 591 firms willing to and suitable to participate in the

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<sup>41</sup> Note that this formulation of sampling error is applicable only for simple binary (yes/no) questions, but it does provide an indication of the sampling error associated with a certain sampling size.

study. Surveys were mailed to each of these firms, and 259 of them replied. In each stage of this process, it was possible to introduce a bias into the sample, referred to by Dillman (2000) as a non-response error. For example, it is possible that the proportion of large firms in the final population is much higher than it was in the initial population. If this is the case, the survey responses from the final population cannot be considered fully representative of the complete initial population.

To investigate potential biases in the process described, the population at each stage in the process can be compared. Table 6 shows the process according to which SIC category each firm in the population belongs to. Although the first stage of the process does not initiate any significant biases (it is a random sample and should not be expected to initiate biases), both the telephone survey and the mail survey generate higher response rate among firms in SIC 20, 26, 28, and 29 and a lower response rate in SIC 22, 33, 35, and 38. These biases are likely due to the fact that firms in the over-represented sectors were more likely to use steam in their processes than firms in the under-represented sectors and were therefore more likely to qualify for the survey. The food, chemical, pulp and paper, and refining sectors all use significant amounts of steam in their processes (for sterilization, drying, and high temperature reactions), while equipment manufacturers use much less (steam, if used, is primarily for space heating). Firms using more steam in their processes would likely be more interested in participating in this survey, which could also help to explain the higher response rate among these sectors.

**Table 6 - Survey biases by SIC**

<b>SIC</b>	<b>Total in Sample</b>	<b>Total Called</b>	<b>% Called</b>	<b>Total Participants</b>	<b>% Participants</b>	<b>Total Responding to Mail Survey</b>	<b>% Responding to Mail Survey</b>
20	1907	1784	93.6%	257	14.4%	104	40.5%
22	113	102	90.3%	8	7.8%	3	37.5%
24	1175	1108	94.3%	79	7.1%	34	43.0%
26	641	603	94.1%	44	7.3%	25	56.8%
28	831	791	95.2%	97	12.3%	44	45.4%
29	198	189	95.5%	18	9.5%	6	33.3%
30	1021	955	93.5%	30	3.1%	13	43.3%
31	65	60	92.3%	5	8.3%	1	20.0%
33	428	404	94.4%	7	1.7%	4	57.1%
35	954	896	93.9%	9	1.0%	5	55.6%
38	391	360	92.1%	4	1.1%	2	50.0%
<b>Others</b>	1359	1289	94.8%	33	2.6%	18	54.5%
<b>Total</b>	9083	8541	94.0%	591	6.9%	259	43.8%

Table 7 shows the bias in the survey process according to the number of employees in a company. Again, as expected, the random sample did not introduce significant bias into the population. However, in both the telephone survey and the mail survey, large firms were more likely to respond to the survey than small firms. There are two probable explanations for this. First, large firms have more capacity to respond to surveys than do small firms. In a similar study of energy efficiency in Canadian industry, Takahashi et al. (2002) report that proportionately more large firms than small firms responded to their survey. Second, large firms are more likely to use steam in their processes than small firms.

**Table 7 - Survey biases by number of employees**

<b># Employees</b>	<b>Total in Sample</b>	<b>Total Called</b>	<b>% Called</b>	<b>Total Participants</b>	<b>% Participants</b>	<b>Total Responding to Mail Survey</b>	<b>% Responding to Mail Survey</b>
20-50	4771	4503	94.4%	256	5.7%	92	35.9%
51-150	2781	2594	93.3%	184	7.1%	91	49.5%
151-500	1258	1184	94.1%	117	9.9%	54	46.2%
500 +	273	260	95.2%	34	13.1%	22	64.7%
<b>Total</b>	9083	8541	6.0%	591	6.9%	259	43.8%

Table 8 shows the survey process segregated according to the revenue of firms in the survey. Again, the random sample introduced no bias. Similarly to the previous segregation however, the other two survey stages did introduce some bias. Firms with large revenues were more likely to respond to the last two survey stages than firms with low revenues. Reasons for these biases are parallel to the reasons discussed above: large firms have more capacity to respond to surveys and more interest in steam generating technologies.

**Table 8 - Survey biases by firm revenue**

<b>Revenue (Million \$)</b>	<b>Total in Sample</b>	<b>Total Called</b>	<b>% Called</b>	<b>Total Participants</b>	<b>% Participants</b>	<b>Total Responding to Mail Survey</b>	<b>% Responding to Mail Survey</b>
<b>0-1</b>	102	9	91.2%	1	1.1%	1	100.0%
<b>1-10</b>	5054	302	94.0%	239	5.0%	81	33.9%
<b>10-100</b>	2945	176	94.0%	267	9.6%	132	49.4%
<b>Over 100</b>	330	14	95.8%	43	13.6%	25	58.1%
<b>N/A</b>	652	41	93.7%	41	6.7%	20	48.8%
<b>Total</b>	<b>9083</b>	<b>542</b>	<b>94.0%</b>	<b>591</b>	<b>6.9%</b>	<b>259</b>	<b>43.8%</b>

Clearly, there are some biases present in the survey. Large firms are over represented in the results, as are firms in the food, petroleum refining, chemicals, and pulp and paper sectors. While it is not possible to directly quantify the error that such biases introduce into the results, it is important to recognize that such an error probably does exist.

In addition to error due to biases, there is also error associated with measurement (Dillman 2000). Measurement error results when survey respondents misinterpret questions or give deliberately incorrect answers. Measurement error in this survey is potentially significant because the choice experiment does not closely approximate the real decision-making process that would underlie the purchase of steam generating equipment in industry. Undoubtedly, the process would involve a committee within the firm and would likely be at least partially dictated by non-financial concerns<sup>42</sup>. Such a

<sup>42</sup> For example, a firm's decision is likely to be influenced by the knowledge and expertise available in the firm, as well as perceptions of safety, maintenance requirements, and availability of distributors. Further, it is theorized that groups making a decision can suffer from collective action problems, where the many

process could produce choice outcomes significantly different than those recorded in this survey. Again, it is impossible to quantify this error, yet important to recognize its presence.

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stakeholders actually reduce the effectiveness of the decision-making process; the whole becomes less than the sum of its parts.

## 4. Results and analysis

### *4.1 Qualitative findings on industrial cogeneration*

Of the 259 firms responding to the mail survey, 21, or 8.1%, identified themselves as using a cogeneration system in their plant. There are currently 124 known cogeneration facilities in Canada (CIEEDAC 2002), meaning that about 8.6% of potential cogenerators actually employ a cogeneration system in their plant<sup>43</sup>. The close match between the ratio of cogenerating plants in this survey and in reality suggests that the biases discussed in the previous chapter had relatively little effect on the survey results.

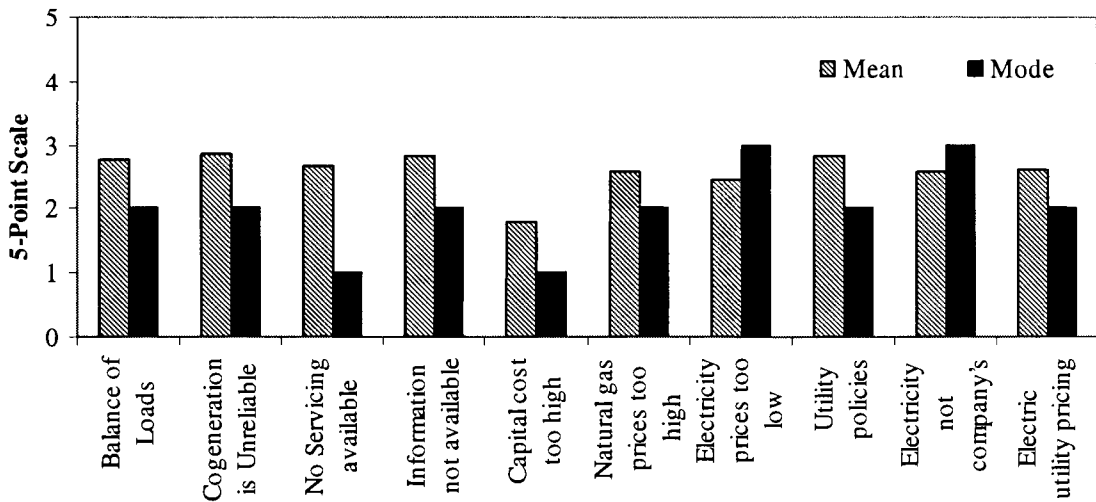
Although only 8.1% of the firms in the sample currently employ a cogeneration facility in their plant, about one quarter (25.4%) indicated that cogeneration had previously been considered in their plant. Further, about one third (31.9%) stated that cogeneration would be considered in the future if equipment turnover or plant expansion dictated the need for new heating investment. These results show that even where cogeneration is considered in industry it is adopted only about one third ( $8.1\%/25.4\% = 31.8\%$ ) of the time. Figure 8 shows how firms explain their decision not to cogenerate. Not surprisingly, financial concerns are perceived to be an important barrier, with capital costs, natural gas prices, electricity prices, and electric utility pricing policies all showing up as important reasons why a cogeneration plant was not purchased.

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<sup>43</sup> To estimate the total number of potential cogenerators in Canada, the number of firms in the sectors identified in Table 2 is adjusted by multiplying by the ratio of qualifying (steam-using) firms to non-qualifying (non-steam using) firms. This gives a total potential of  $9083 \times (6.9/(36.6+6.9))=1441$  firms. The ratio of actual cogenerators to potential cogenerators is then  $124/1441 = 8.6\%$ .

**Question 12. If your plant does not currently use a cogeneration systems, how important are each of the following factors in preventing your plant from using a cogeneration system?**

*In this question, 1 means that the respondent feels that the factor is a 'very important' factor preventing cogeneration in the firm, while 5 means that the factor is 'completely unimportant'.*



**Figure 8 - Perceived barriers to cogeneration**

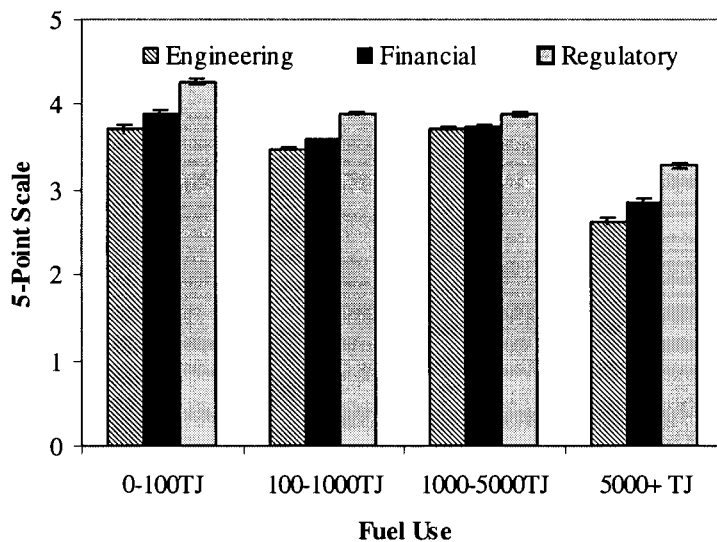
In the above discussion, it was mentioned that cogeneration has only been considered by about one quarter of the plants in the survey, even though all plants responding to the mail survey are potential cogenerators (all use steam for either process or space heating in their plants). This low consideration of cogeneration likely reflects a lack of knowledge or familiarity with cogeneration. Indeed, only 34.6% of respondents reported that they knew of any industrial plants in their sector that had an active cogeneration facility. As would be expected from such a low familiarity with cogeneration, knowledge of the important technical, financial, and regulatory issues surrounding cogeneration is also low. Figure 9 shows how respondents rated their current level of knowledge regarding cogeneration issues. The chart is broken into categories based on the amount of fuel



consumed in the plant<sup>44</sup>. As expected, smaller consumers of energy are less well informed about issues surrounding cogeneration than large consumers of energy. Even among large plants, however, general knowledge of cogeneration issues is low. All firms were more confident in their knowledge of the technical issues surrounding cogeneration than the financial and regulatory issues.

**Question 6. Please mark the box that best describes your current state of knowledge of cogeneration technologies in each of the following categories.**

*For this question, 1 means that the respondent is 'very well informed' about cogeneration, while 5 means that the respondent is 'uninformed' about cogeneration.*



**Figure 9 - Perceived knowledge of cogeneration by fuel consumption<sup>45</sup>**

<sup>44</sup> Similar breakdowns were performed by electricity use and by sector. Each showed that firms more likely to use cogeneration (large users of fuel, large users of electricity, firms in petroleum refining, chemicals, and pulp and paper sectors) were more informed about cogeneration than other firms.

<sup>45</sup> TJ – Terajoule –  $10^{12}$  Joules

The survey shows that cogeneration technology is a poorly understood technology that many plant managers are unfamiliar with. This is particularly evident in smaller firms. De Groot et al. (2001) found similar trends in their survey of general energy efficiency investments in Dutch industry. In particular, they found that a significant portion of firms surveyed have no knowledge of any energy efficiency measures used by firms in the Netherlands. They also found that small firms have much less knowledge of energy efficiency measures than do large firms, and that firms in highly competitive sectors have increased knowledge of energy efficiency measures, presumably because competition forces them to look for investments that save operating costs.

Such a limited familiarity and knowledge of cogeneration suggests that there could be a role for demonstration projects, information programs, and moral suasion campaigns aimed at increasing the visibility of cogeneration to firms in the Canadian economy. The public goods nature of information makes government a well-suited provider of such programs (de Groot et al. 2001; DeCanio 1993). Such projects should be aimed especially at increasing the familiarity of cogeneration to plant managers in smaller companies<sup>46</sup>.

The survey also polled firms on their receptiveness towards different types of policy instruments, ranging from less restrictive instruments like information programs and subsidies to more restrictive programs such as technology regulations and taxes. It is generally believed that firms prefer to operate in a market free of government intervention, and if an intervention is needed that it should be as non-restrictive as possible (Pal 2001). Answers to this question, shown in Figure 10, confirm this belief. Information provision and subsidies are perceived as very acceptable policies for promoting energy efficiency, while taxes and technology standards are perceived as generally unacceptable ways to promote energy efficiency in firms. Recycled energy taxes, where revenue generated from energy taxes is used to offset labour or other taxes,

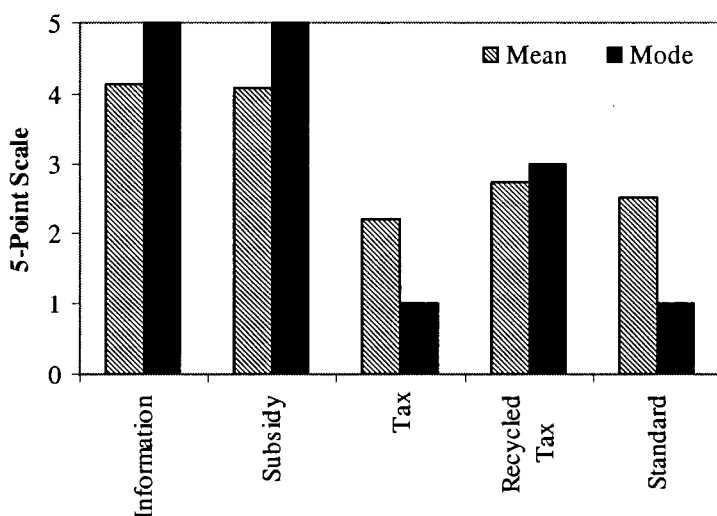
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<sup>46</sup> In Chapter 2 I discuss how information campaigns are by no means universally successful, and care needs to be taken in their design and implementation.

were seen as fairly neutral to the firms surveyed. De Groot et al. (2001) report similar perceptions about policies for firms in the Netherlands.

**Question 18. There are many policies that the Government could use to affect the energy efficiency of industry. Rate each of the following policies according to how acceptable they would be to your plant.**

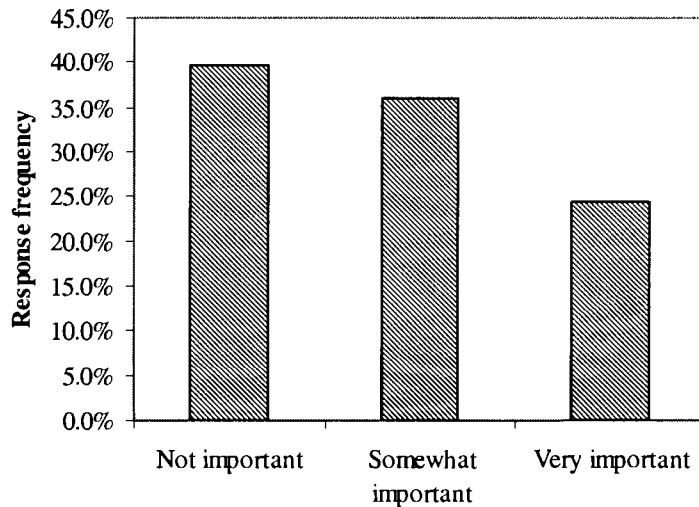
*In this question, 1 means that the policy is 'completely unacceptable' and 5 means that the policy is 'completely acceptable'.*



**Figure 10 - Acceptability of policy instruments to firms**

Due to the high degree of integration between the Canadian and American economies, policies that affect the cost of production of Canadian firms can potentially have significant implications for competitiveness across the border. Figure 11 shows firms' perceptions about how important it is that Canadian energy policies are comparable to American energy policies. Interestingly, most firms felt that it was relatively unimportant that Canada's energy policies are comparable to the US, and that Canada should develop its energy policies based on its own needs.

**Question 19. How important is it that Canada's energy efficiency policies are comparable to those of the United States?**



**Figure 11 - Importance of maintaining similarity between Canadian and US energy policy**

These qualitative findings on industrial policy preferences are important for the design of public policies aimed at improving energy efficiency in industry. The political feasibility of a policy is at least as important to government as its projected effectiveness in determining whether or not to implement it. Politicians are extremely reluctant to implement policies unpopular in the business community, both out of fear of hurting industrial competitiveness and out of unwillingness to alienate their constituency.

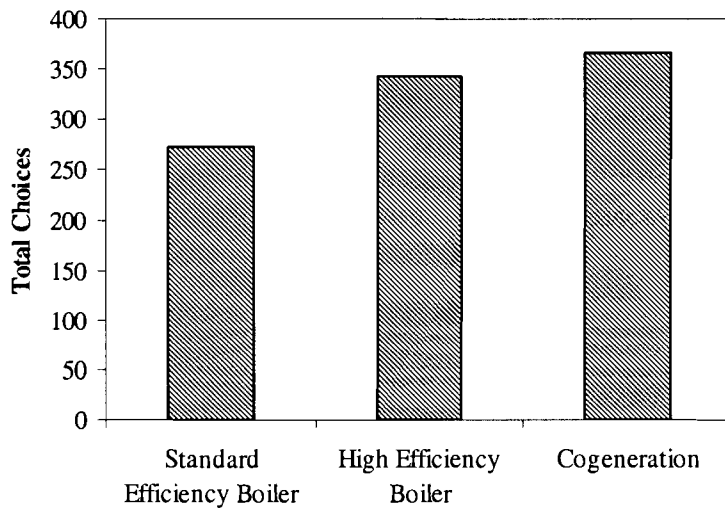
#### ***4.2 Discrete choice experiment***

The discrete choice model is based on stated choices made by respondents from the three choices available to them – the standard efficiency boiler, high efficiency boiler, and cogeneration system. A well-designed experiment will have attribute levels set so that no one choice is dominant in all cases<sup>47</sup>. The result of a well-designed experiment should be

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<sup>47</sup> In a poorly designed experiment, the levels are inappropriately set so that one choice always is the clear favourite. In this case, it becomes impossible to estimate the discrete choice model coefficients correctly.

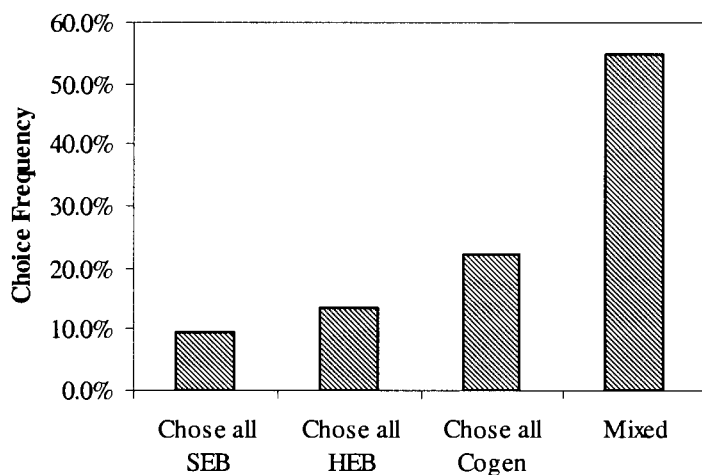
a relatively even spread of choices from the available alternatives. Figure 12 shows the spread of choices made by respondents in this survey. Clearly, all alternatives received a significant number of choices, which suggests that the attributes were set at reasonable levels, and that no alternative was dominant.



**Figure 12 - Choice frequency in the discrete choice experiment**

A detailed analysis of the spread of choices made at the individual level, however, reveals a possible cause for concern. Figure 13 shows that about 35% of survey respondents made the same choice in each of the four discrete choice experiments presented to them, despite the fact that the attribute levels of each alternative were different in the four choices. This could suggest that although no one choice was dominant throughout the population, some choices were dominant for some individuals. A reason for this could be that decision makers are relying too heavily on their preconceptions rather than objectively considering the alternatives in the choice set in a dispassionate manner. Alternatively, this phenomenon could suggest that the discrete choice experiment was poorly understood or that respondents did not take the time to thoroughly consider each of the four choice experiments before responding. A discussion of individual level choice dominance could not be found in the discrete choice literature, so it is not clear whether this is a common phenomenon in such experiments or whether it is cause for concern in

the interpretation of results. This paper proceeds by assuming that this phenomenon is not a cause for concern.



**Figure 13 - Individual level choice distributions**

Attribute coefficients for the discrete choice model were estimated using continuous attribute coding with LIMDEP 7.0<sup>48</sup>. 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<sup>49</sup>. Coefficient estimates and statistical significance (t-test values) for the discrete choice model (Equation 8) are presented in Table 9.

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<sup>48</sup> Continuous attribute coding means that the model was estimated using actual attribute levels rather than their discrete (also called ordinal) alternatives.

<sup>49</sup> 976 responses from 260 surveys works out to only 3.75 responses per survey. This is because some respondents did not fill out some or all of the choice questions.

**Table 9 - Discrete choice model**

<b>Coefficient</b>	<b>Value</b>	<b>t-test</b>
Capital Cost	-2.16E-07	-2.924
Operating Cost	-9.67E-08	-0.064
Fuel Cost	-1.51E-07	-1.325
Electricity Savings	6.87E-07	8.051
ASC – Standard Efficiency Boiler	-0.261	-2.110
ASC – High Efficiency Boiler	0.225	2.320
$L(0)$	-1072.245	
$L(a)$	-1065.201	
$L(\beta)$	-1016.098	
$L(\beta)/N$	-1.042	
$-2*(L(\beta) - L(0))$	$x^2 = 112.294$ with 6 d.o.f.*	
$-2*(L(\beta) - L(a))$	$x^2 = 98.206$ with 4 d.o.f.*	
$\rho = 1 - L(\beta)/L(0)$	0.0524	

\* Both of these Chi-squared tests are significant at the 99.9% confidence level.

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 savings increase the utility. The alternative specific constants (ASC's) show that standard efficiency boilers are less preferred than cogeneration (which has an ASC of 0) *ceteris paribus*, while high efficiency boilers are more preferred than both cogeneration and standard efficiency boilers *ceteris paribus*.

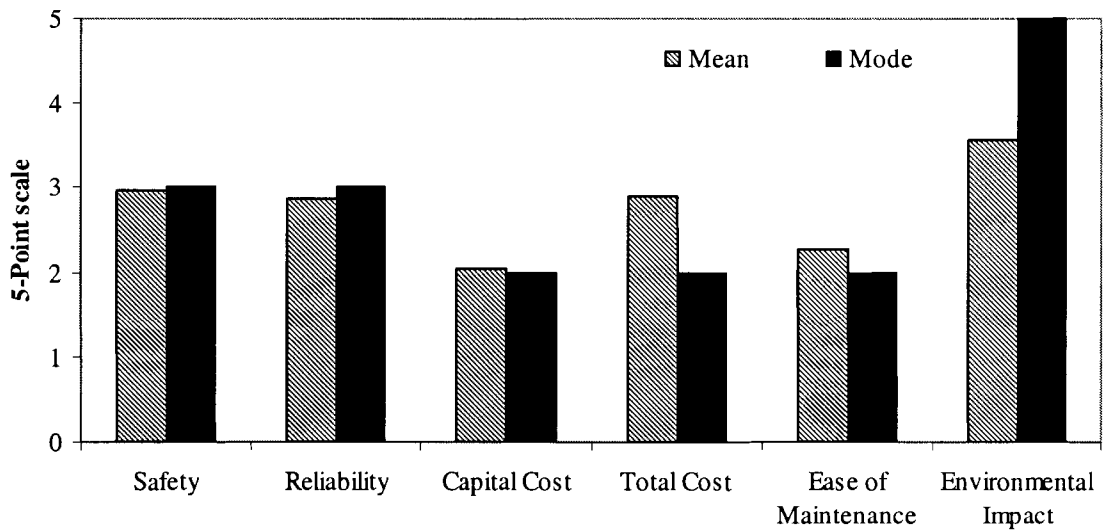
All coefficients are significant at the 90% confidence level except for the operating cost coefficient. This is not surprising, because in general the operating cost was dwarfed by other costs in the choice experiment, and so probably had less influence on the choice outcome than the larger costs. For 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.

Some insight into the reason for the signs of the alternative specific constants can be gained from respondents' answers to the qualitative question in the survey dealing with relative preferences for boilers and cogeneration systems. Figure 14 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 boilers are easier maintained than cogeneration systems (the high efficiency boilers have a lower environmental impact than standard efficiency boilers).

**Question 14. How do you feel cogeneration systems compare to conventional boiler systems in each of the following categories?**

*In this question, 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.*



**Figure 14 - Comparison of cogeneration with boiler**



The scale of the ASC's relative to the total utility indicates the importance of attributes not included in the discrete choice experiment. For a small firm (e.g., 1 MW<sub>th</sub> demand), the ASC is a dominant component of the total utility (up to about 30% of the total utility), while for a large firm (e.g., 50 MW<sub>th</sub> demand) the ASC is a relatively small component of the total utility (as low as 5% of the total utility). This reflects the increased propensity of small firms to choose high efficiency boilers (the only alternative with a positive ASC) over the alternatives, regardless of the costs of doing so. Large firms, meanwhile are shown to base decisions more on cost than on systematic preferences relating to specific technologies.

The results in Table 9 also describe how well the model fits the data set. Goodness-of-fit is assessed using the log of the likelihood, a negative variable that gets closer to zero with increasing model validity. For a perfect DCM (i.e., one that always predicts the choice that was actually made), the log likelihood would be zero. Unfortunately, the log likelihood value is meaningless on its own, because it decreases (gets more negative) with the number of samples in the data set, so it is not used as a direct test of model fit. Instead, the common assessment of goodness-of-fit is performed by comparing the log likelihood of the model to that of a model with all parameters set to zero (equivalent to not having a model at all) as in Equation 11:

$$\rho = 1 - \frac{LL(\beta)}{LL(0)} \quad (11)$$

In Equation 11,  $\rho$  is referred to as the likelihood ratio index (Train 2002). It can take on values from 0 to 1, with 0 indicating that the estimated model has no more predictive capacity than no model at all, and 1 indicating that the model is so good that it can predict each decisions maker's choice perfectly. The likelihood ratio test should not be confused with the  $R^2$  test used for regression analysis. While both have the same range and general purpose,  $R^2$  shows the percentage variation in the dependent variable explained by the model, while  $\rho$  has no such intuitive interpretation for values other than 0 or 1. In fact,  $\rho$  cannot be compared from one model to another and no meaningful comment can be made

about the magnitude of  $\rho$  values between 0 and 1. The likelihood ratio index for this model is 0.0524.

A similar goodness-of-fit test for the model involves statistically testing whether the model is better than a model with all coefficients equal to zero (no model at all), or a model with all coefficients except alternative specific constants equal to zero (restricted model). Again, the comparison is made through the likelihood values of the various models. To test whether the difference between the full and restricted models is significant, we make use of the fact that twice the difference between the log likelihood of two models is chi-squared distributed, with the number of degrees of freedom equal to the number of explanatory variables in the full model minus the number in the restricted model. If the full model is a better fit than the restricted model, twice the difference in their log likelihoods will exceed the critical value of the chi-squared distribution with the appropriate number of degrees of freedom. For the model described in Table 9, the full model (with all coefficients) is significantly different from both the restricted model and no model at all at the 99.9% confidence level.

With the model parameters estimated, it is possible to predict the new market shares of the three technologies given their attribute levels. Table 10 shows the attribute levels for a standard efficiency boiler, high efficiency boiler, and cogeneration system which each produce 12 MW of thermal energy (steam) using natural gas as a fuel source.

**Table 10 - Sample technology attribute levels for 12 MW<sub>th</sub> output**

<b>Technology</b>	<b>Capital Cost</b>	<b>Operating Cost</b>	<b>Fuel Cost</b>	<b>Electricity Savings</b>
Standard Efficiency Boiler	\$2,897,000	\$121,000	\$1,000,000	\$0
High Efficiency Boiler	\$4,345,500	\$172,500	\$900,000	\$0
Cogenerator	\$5,537,000	\$233,000	\$1,000,000	\$200,000

Based on these attribute levels, the DCM predicts that standard efficiency boilers capture 33.0% of the market, high efficiency boilers 39.6%, and cogeneration systems, 27.6%.

The prediction that cogeneration systems capture over one quarter of the steam generation market share is significantly higher than in reality, where about 8-9% of firms cogenerate (in the sectors being analysed). Possible reasons for the divergence could be that the costs of the technologies are not accurate, or that firms perceive that the real costs are different than those in Table 10 and Appendix 5. The difference could also be due to the fact that the current cogeneration market share is based on as much as 50 years of accumulated industrial choices, while this survey is based on hypothetical choices made this year. It is possible that preferences towards alternative steam generation technologies have changed significantly during this time and that the survey results are more indicative of future potential for cogeneration than is the historical market share. Another potential reason for the difference is that the analysis is based on firms' stated choices, rather than on revealed choices in the market. Consequently, the model might not be indicative of real choices in the market place. The difference could also be due to the fact that the choice sets presented to respondents in the survey were not the same as the choice sets they construct when making the decision in reality. Only about one third of the firms in the survey indicated that cogeneration had been considered in their plant, implying that it was not in the choice set for the remaining two thirds of plants surveyed. This would skew the survey results in favour of cogeneration significantly. Finally, it is likely that the utility function used in this choice experiment does not fully capture the attributes that are important to industrial steam generation decision-making. In particular, the utility function includes only financial cost parameters (the exception being that the alternative specific constants can capture non-financial preferences) and it is probable that non-financial costs are important elements of this decision.

### **Elasticity estimates and policy relevance**

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 derivative of the choice

probability is calculated – this value shows the change in choice probability per change in attribute value and is calculated using partial derivatives (Train 2002)<sup>50</sup>:

$$\frac{\partial P_i}{\partial x_z} = \frac{\partial(e^{V_i} / \sum_j e^{V_j})}{\partial x_z} = \beta_z P_i(1 - P_i) \quad (12)$$

Table 11 shows the change in choice probability of each alternative given a \$1,000,000 increase in attribute value *starting from the base attribute levels* in Table 10. 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.

**Table 11 - Cost elasticities from the discrete choice experiment**

Technology	Effect of a \$1,000,000 increase in:			
	Capital Cost	Operating Cost	Fuel Cost	Electricity Savings
SEB	-0.0477	-0.0214	-0.0334	-
HEB	-0.0517	-0.0231	-0.0361	-
COG	-0.0430	-0.0193	-0.0301	0.1368

Table 11 reveals two lessons regarding relative attribute importance that are critical to effective policy design. First, by comparing the capital cost elasticities to the annual cost elasticities, 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 savings). 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

<sup>50</sup> Economists typically normalize these derivatives to eliminate variable units. Elasticities are simply the percentage change in one variable that results from a one percent change in another variable. However, in this study, all variables are in the same units (dollars), and so it makes more sense to present the choice derivatives inclusive of units. To avoid confusion, I use the term elasticity in this paper to refer to the partial derivative of the choice probability (not normalized).

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. Clearly, manipulating the capital cost is a more effective manner to encourage cogeneration than manipulating the operating cost<sup>51</sup>. At least part of the reason for the discounting of annual cost savings with respect to capital cost savings by firms is likely to be due to risk aversion, as discussed in Chapter 2.

Second, in comparing the three annual cost elasticities (operating cost, fuel cost, and electricity savings), we see that the highest leverage point for policy is manipulating the electricity savings, rather than the fuel or operating costs. A \$1,000,000 increase in electricity savings affects the choice probability over six times as much as an equivalent savings in operating costs, and over four times as much as an equivalent fuel cost savings. Most techno-economic analyses of cogeneration (and other technologies) treat similar types of costs in the same way; for example, they assume that consumers are indifferent to a \$1 increase in fuel costs versus a \$1 increase in operating and maintenance costs (see, for example, Joskow and Jones 1983; Rose and McDonald 1991). The DCM estimated here, however, shows that consumers feel differently about different types of costs; in particular, they value savings in electricity very highly. A possible reason for the premium that firms place on offset electricity is the high value obtained from partial independence from the electricity grid. 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 by orders of magnitude. Power outages can cost industrial firms millions of dollars in lost revenue and damages, and so firms will pay a high cost to avoid them.

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<sup>51</sup> The elasticities described in Table 12 are only applicable to the technologies described in Table 11; while the lessons for all size ranges remain the same, the actual numbers will differ.

## Model segregation

The model in Table 9 assumes that there is no systematic (non-random) variation in tastes within the population being modeled – it is a model of a “representative” firm within the population<sup>52</sup>. However, it is possible that there are systematic variations of tastes within the population. Large firms, for example, could place different values on costs than small firms. Alternatively, firms in the pulp and paper sector could find cogeneration more attractive than firms in other sectors. In these cases, the assumptions underlying the multinomial logit DCM cease to hold, and the model becomes less valid. To account for this type of phenomenon, discrete choice modellers take one of two approaches to develop improved discrete choice models based on subgroups of the population (Meyer and Kahn 1993):

1. They expand the utility function to include parameters representing characteristics for each individual
2. They segregate models based on different consumer segments, each homogeneous with respect to a set of consumer characteristics.

In order to attempt to develop a more realistic model, this study takes the second approach and segregates the model on several characteristics. Table 12 shows the different segregated models. The particular segregations shown in Table 12 were chosen because it was hypothesized that there could be a significant difference in the utility function parameters between the two groups in each segregated model. In the first segregation, which divides the model into one group consisting of firms in the petroleum refining, chemicals, and pulp and paper sectors, and another group consisting of all other firms, it was expected that the first group would have a systematically higher preference for cogeneration than the second group<sup>53</sup>. In the second segregation, firms were divided

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<sup>52</sup> Systematic variation would imply that variations between members of the population could no longer be described using independent Type I Extreme Value distributions.

<sup>53</sup> Recall that firms in these three sectors make up more than 75% of the total cogeneration capacity in Canada (MKJA 2002).

into high users of fuel and low users of fuel, with the expectation that large fuel users would have more incentive to cogenerate than small fuel users. In the third segregation, firms were divided into those who felt that they were well informed about cogeneration and those who felt they were poorly informed about cogeneration. Obviously, the expectation was that firms well informed about cogeneration would exhibit greater preference for that technology<sup>54</sup>.

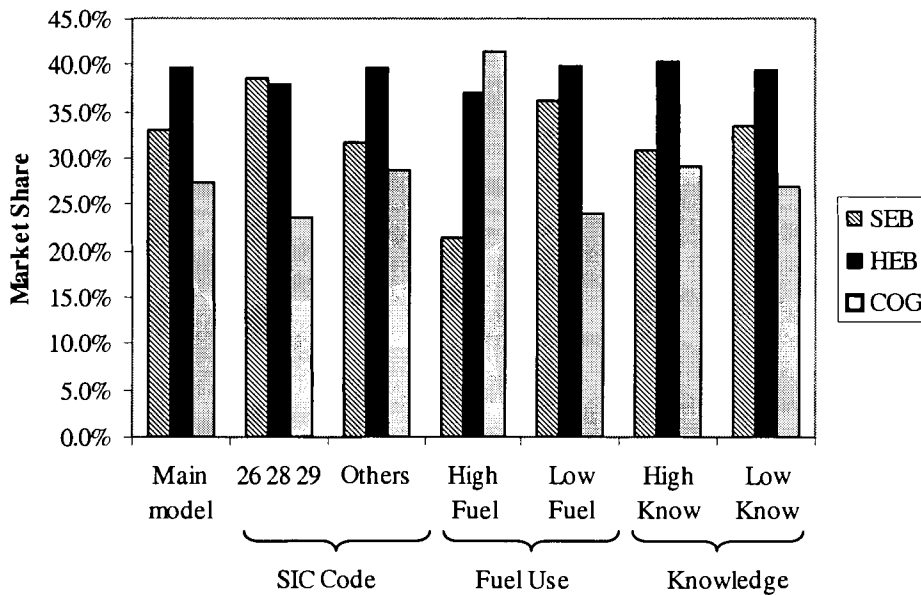
**Table 12 - Model segregation**

Variable	SIC Code		Fuel Use		Knowledge	
	26, 28, 29	All Others	High (Above 25 GWh/y)	Low (Below 25 GWh/y)	Informed	Not Informed
CC	-6.46E-08	-3.09E-07*	-1.34E-07	-3.03E-07*	-1.81E-07	-2.31E-07*
OC	-3.56E-06	1.82E-06	-6.02E-07	4.34E-07	-3.45E-07	-5.03E-08
FC	-2.12E-10	-4.37E-07*	3.49E-08	-3.06E-07	-2.83E-07	-7.90E-08
ES	7.98E-07*	6.28E-07*	2.87E-07*	1.12E-06*	6.15E-07*	7.34E-07*
SEB	8.31E-02	-0.383*	-1.026*	-0.116	-0.337	-0.255*
HEB	0.345*	0.147	-0.244	0.370*	0.182	0.241*
N	282	694	136	840	178	798
$L(\beta)_i$	-274.4304	-735.7442	-133.6418	-869.4655	-176.2041	-838.9248
$L(\beta)_1+L(\beta)_2$	-1010.1746		-1003.1073		-1015.1289	
$\chi^2$	$\chi^2 = 11.8468$ with 6 dof		$\chi^2 = 25.9814$ with 6 dof		$\chi^2 = 1.9382$ with 6 dof	

\* Indicates that the coefficient is significant at the 95% confidence level.

Figure 15 shows the predictions resulting from each model for the technologies described in Table 10. Firms which use a large amount of fuel are predicted to be almost twice as likely to use cogeneration as firms which use a small amount of fuel. Similarly, firms that are well informed about cogeneration are predicted to be more likely to use cogeneration than firms poorly informed about the technology. Surprisingly, however, firms in SIC 26, 28, and 29 are predicted to be less likely to cogenerate than firms in other industrial sectors.

<sup>54</sup> Because the firm characteristics were not part of the experimental design, it is highly likely that the segregations are correlated with each other. For example, many of the firms with high knowledge of cogeneration are likely in SIC 26, 28, or 29. Consequently, it is difficult to assign difference between the two models exclusively to the particular segregation.



**Figure 15 - Technology market shares predicted by segregated models**

The chi-squared test (as discussed previously) is used to test whether each segregated model offers better explanatory power than the non-segregated model in Table 9. The segregated model is said to be significantly different (i.e., better) than the original model if twice the difference in their log-likelihoods exceeds the critical value of the chi-squared distribution at the required confidence level. The critical value of the chi-squared distribution at the 95% confidence level with 6 degrees of freedom is 12.592. At this confidence level, only the segregation by fuel use offers significantly better explanatory power than the base model.

Unfortunately, this exercise in model segregation is made difficult for the current data set due to its small size. Louviere et al. (2000) recommend obtaining at least six observations (data points) at each unique combination of attributes. With the experimental design described in chapter 3, this entails  $32 \times 6 = 192$  observations. Because the mail surveys were simultaneously administered, getting six observations at each data point actually entails obtaining significantly more than 192 observations for each model. As can be seen from Table 12, all of the segregated models have at least one



segregation with a small number of observations (282, 136, and 178 for the three models). Consequently, many of the attribute coefficients are not statistically significant.

Despite the lack of statistical significance, segregating the models does expand potential for policy analysis. In particular, estimating separate models for respondents who are well informed about cogeneration versus those who are not provides the ability to test the effect of a program to raise awareness of cogeneration among those currently unfamiliar with the technology.

## Uncertainty

Throughout the above discussion, parameters estimated from the data have been treated as certain – they represent the best estimate at a utility model for the choice described. However, the parameters shown are only the most likely parameter estimates for the utility model based on the data set; there are many other parameter combinations that are possible, although less likely. To understand why this is the case, it is instructive to understand the procedure for estimating the model parameters from the data set.

Parameters are estimated using a Newton-Raphson optimization routine, which is an iterative search for the  $\beta$  parameters that provide the best model fit. The best-fitting  $\beta$  parameters maximize the log likelihood function<sup>55</sup>. The log likelihood of any particular combination of  $\beta$  parameters is:

$$LL(\beta) = \sum_{n=1}^N \frac{\ln(P_{n,j}(\beta))}{N} \quad (13)$$

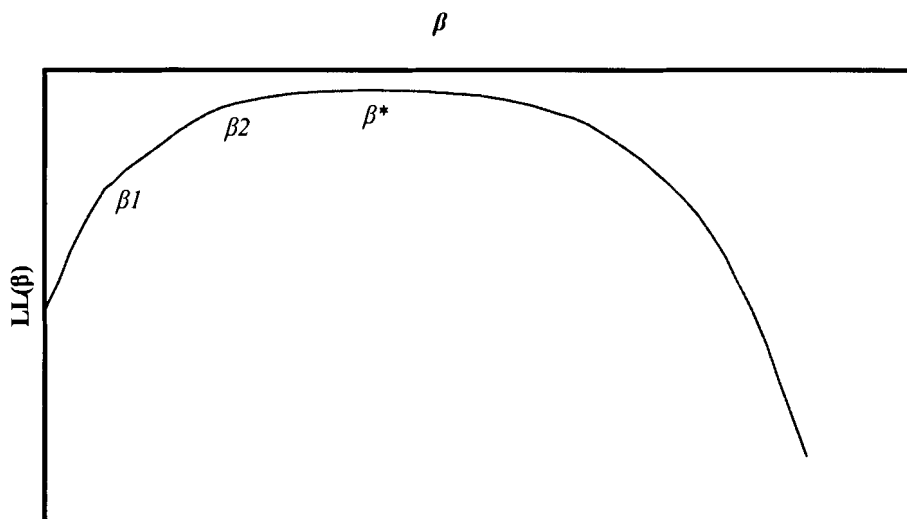
where  $N$  is the number of observations in the data set and  $P_{n,j}(\beta)$  is the probability that the model assigns to the choice  $j$  that was actually made by the respondent at observation  $n$

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<sup>55</sup> The model works with log likelihoods rather than strict likelihoods because the magnitudes of the former are more manageable.

with the particular combination of  $\beta$  parameters being tested.  $P_{n,j}(\beta)$  is calculated using the multinomial logit model (Equation 7).

In order to find the combination of  $\beta$  parameters that maximize this function, the Newton-Raphson routine “walks up” the log likelihood function from starting values of  $\beta$  parameters until no further increases can be found<sup>56</sup>. The N-R routine determines what direction to “step” by calculating the first derivative of the log likelihood function (the gradient matrix) and how far to “step” by calculating the second derivative of the log likelihood function (the Hessian matrix). The routine continues to “walk up” the log likelihood function until the “steps” become sufficiently small. At this point, the algorithm has found the maximum likelihood estimator for the data set – that set of  $\beta$  parameters that best fits the data. Figure 16 illustrates this process for a utility function with one parameter (graphical illustration of cases for more parameters is difficult). As can be seen from Figure 16, while  $\beta^*$  is the most likely parameter value, many other estimators exist that have significant likelihood.



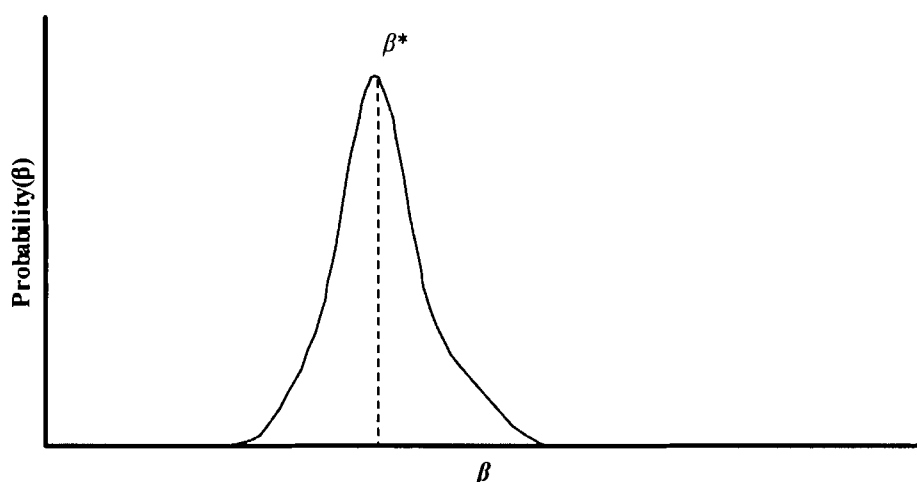
**Figure 16 - Log likelihood function**

<sup>56</sup> Walking up the utility function is possible for a linear-in-parameters multinomial logit model (as is the case in this study) because the log likelihood function is globally concave – meaning that there are no local maxima or minima.

The likelihood distribution for  $\beta$  can easily be translated into a corresponding probability density function by scaling the exponent of the log likelihood of each possible  $\beta$  by the sum of the exponents of the log likelihood at all other possible values of  $\beta$ :

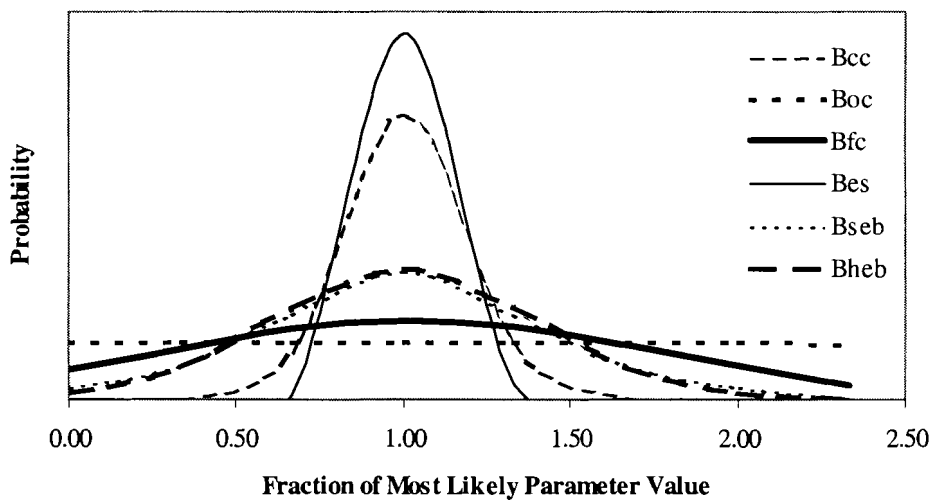
$$\Pr(\beta_i) = \frac{e^{LL(\beta_i)}}{\sum_{j=1}^J e^{LL(\beta_j)}} \quad (14)$$

Figure 17 is the probability density function (pdf) for  $\beta$  corresponding to the log likelihood function in Figure 16. The peak of the pdf ( $\beta^*$ ) corresponds to the peak of the log likelihood function. From Figure 17, however, it can readily be seen that  $\beta^*$ , while being the most probable value for  $\beta$ , is not the only possible value. Ignoring all potential values of  $\beta$  other than  $\beta^*$  will lead to biased and incorrect modelling results and consequent policy recommendations (Morgan and Henrion 1990). Including these other values of  $\beta$  in modelling exercises makes better use of the available data by not ignoring uncertainty in the parameter estimates.



**Figure 17 - Probability distribution**

In order to conduct this type of uncertainty analysis for the current study, it was necessary to solve Equation 13 for the six-parameter utility function describing respondents' preferences for steam generating technologies. Instead of a simple one-dimensional log likelihood curve as shown in Figure 16 therefore, the uncertainty analysis consisted of mapping a six-dimensional probability density function<sup>57</sup>. Clearly, such a pdf cannot be graphically represented. Instead, Figure 18 shows the marginal probability density functions representing each parameter in the utility function<sup>58</sup>. These distributions correspond to the t-test values in Table 9. The tightest distributions represent those parameters we are most confident in: the electricity savings coefficient and the capital cost coefficient. Less tight distributions around the standard efficiency boiler ASC, high efficiency boiler ASC, and fuel cost coefficient represent parameters for which we are slightly more uncertain. Finally, the near uniform distribution around the operating cost coefficient shows that we are almost completely uncertain about its true value.

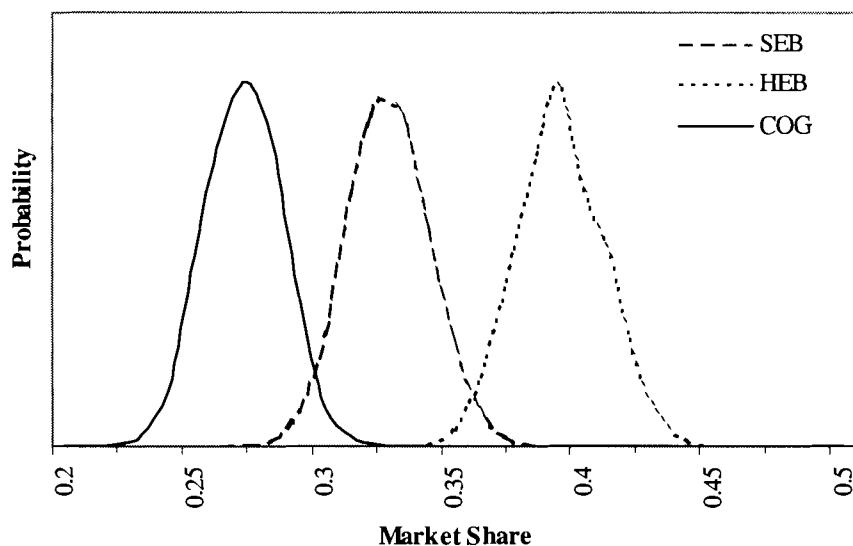


**Figure 18 - Marginal probability density functions for utility function parameters**

<sup>57</sup> This was accomplished using Visual Basic computer code designed to multiply matrices of log likelihood values together.

<sup>58</sup> The marginal probability density function for a variable gives the probability of each value summed across all possible values of each other variable.

Each combination of  $\beta$  parameters has a joint probability density function defined by the log likelihood function (Equation 13) and equivalent to the product of appropriate points on the six marginal probability density functions in Figure 18. Each combination also predicts certain technology market shares given defined technology attribute levels. It is therefore possible to produce new market share distributions, which represent the uncertainty in the DCM predictions, given defined technology attributes. Based on the description of the three technologies found in Table 10, and the projected energy prices given in the CIMS fuel price database, Figure 19 shows probability density functions for the new market shares of the three technologies. Clearly, while the maximum likelihood estimators give average predictions for market share outcomes, they fail completely to represent the range of possible values of market shares. For example, while the most likely market share for standard efficiency boilers is 33%, it is possible that the market share for this technology would be as high as 38% or as low as 28%.



**Figure 19 - Probability distributions showing uncertainty in the model results**

### ***4.3 Informing hybrid energy-economy models using the DCM***

As discussed in the introductory section, discrete choice models on their own are not always useful to policy makers because they do not account for feedbacks throughout the

economy. The above discussion of market share predictions from the DCM, for example, assumes that when a policy is put in place to affect steam generation technologies, everything else in the market remains unchanged. In reality, this would not be the case, particularly if the policy was designed to influence GHG emissions, because any national GHG reduction strategy would seek to simultaneously achieve emissions reductions from throughout the economy. Consequently, the approach taken in this paper is to use the useful information from the DCM in CIMS – an integrated hybrid energy-economy model described in chapter 1. This section presents the results from integrating the DCM into CIMS, and also provides a discussion of how the DCM could be integrated into NEMS, a prominent hybrid model of the US energy economy.

### **Informing CIMS with the DCM**

There are two general approaches for using DCM's to inform CIMS: 1) embedding DCM's directly within CIMS, and 2) revising the current parameters in CIMS based on information from DCM's. The first option would involve replacing the current CIMS technology competition algorithm (Equation 1) with the market share calculation for a discrete choice model (Equation 7). Although the market share equation is generic, the utility formulation would be unique for each node where a DCM is developed. In addition to the current financial cost variables, specific non-cost variables, such as travel time in the transportation example in chapter 1, could be explicitly modeled within CIMS, and could be manipulated directly to simulate various policies. The 'v', 'i' and 'r' parameters would no longer be used, instead being replaced by weighting parameters ( $\beta$ 's) corresponding to each attribute being modeled. This method offers the advantages that none of the information in the DCM is lost in the hybrid model, that a transparent process is used to integrate the survey information into the hybrid model, and that it is easy to translate estimates of uncertainty in the data to the final hybrid model results.

In the second option, the 'r' and 'i' parameters would be calculated from the discrete choice model using valuation techniques, and the 'v' parameter would be solved to equate the market shares between CIMS and the DCM<sup>59</sup>.

The discount rate is calculated through valuation techniques indirectly through the capital recovery factor (CRF). The CRF is the percentage of the capital cost that a consumer would be indifferent to paying annually during the life of a technology instead of the up front capital cost. The CRF can be calculated from a DCM utility function by determining how much the annual cost would have to decrease to leave a consumer indifferent to a one-unit increase in capital cost<sup>60</sup>:

$$\beta_1 CC + \beta_2 OC + \beta_3 I + \beta_i = \beta_1 (CC + 1) + \beta_2 (OC - CRF) + \beta_3 I + \beta_i \quad (15)$$

$$CRF = \frac{\beta_1}{\beta_2} \quad (16)$$

The CRF is related to the discount rate (r) and the life of the technology (n) according to the following relationship:

$$CRF = \frac{r}{1 - (1 + r)^{-n}} \quad (17)$$

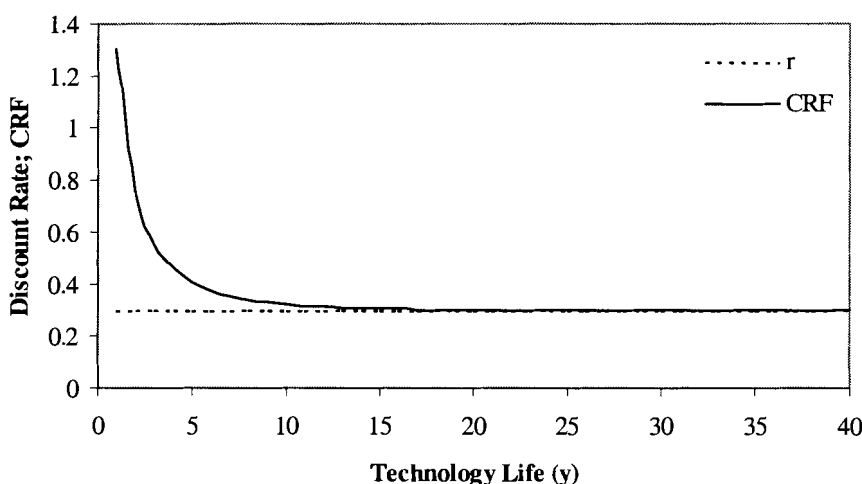
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<sup>59</sup> It is important that if the second option is used, the intangible costs in the CIMS market share equation (Equation 1) are *additive*, rather than *multiplicative*, because only the latter allows the CIMS and DCM market share equations to converge.

<sup>60</sup> In the DCM in Table 10, there were three annual cost parameters instead of the one shown in Equation 15. Because it is not possible to calculate one discount rate based on three annual cost parameters, another DCM was estimated with only one annual cost parameter for the purpose of estimating the discount rate. Using this method to calculate the discount rate loses some DCM information, because the value of all annual costs is treated equally, when the model shows that electricity savings are actually valued higher than operating cost savings, for example.

As the life of a technology gets long, the CRF approximates the discount rate. Figure 20 shows this relationship for a 30% discount rate. As can be seen, for technologies with a lifespan of about 15 years or greater, the CRF and discount rate are equal. Returning to Equation 16, the discount rate for this experiment can therefore be taken to be<sup>61</sup>:

$$r = \frac{\beta_1}{\beta_2} \quad (18)$$



**Figure 20 - Comparison between discount rate and capital recovery factor**

Estimates for 'i' would be obtained in the same manner, with the alternative specific constant and any non-cost variables replacing the capital cost variable in Equation 18<sup>62</sup>.

<sup>61</sup> Steam generating technologies have a lifespan of about 25-50 years.

<sup>62</sup> Direct correlation between DCM's and CIMS in this manner could be hindered by the fact that DCM's work on *differences* in utility, while the CIMS algorithm is based on *ratios* of life cycle costs (see Figures 2 and 3). The ASC's in DCM's are calculated by assuming that one ASC takes an arbitrary value (usually zero), with all others calculated as *differences* from this arbitrary value. In CIMS however, the arbitrary value matters, because of the fact that CIMS deals with *ratios* rather than *differences*. Different choice of initial ASC value will therefore affect the estimation of 'v' in CIMS. In this paper the 'v' parameter was calculated based on the assumption that the arbitrary ASC took on a value of zero (as per convention). This 'v' parameter was estimated over a wide range of attribute levels, so will provide accurate DCM representation of the market share and emissions resulting from various policies, but could diverge from reality for cost estimations. This phenomenon is another argument in favour of 'option 2' above.



It should be stressed that under this option, the non-cost information used to construct the DCM would remain external to CIMS, and sets of 'v', 'i', and 'r' would be estimated from the discrete choice model to simulate various policy scenarios.

The 'v' parameter in the CIMS model is equivalent to the scale of the DCM parameters relative to the error term. For a very homogeneous market (high 'v'), the DCM parameters would dwarf the error terms, while for a more heterogeneous market (low 'v'), the DCM parameters would be of similar magnitude to the error terms.

Unfortunately, there is no direct relationship between the scale of the DCM and the 'v' parameter in CIMS. To calculate 'v', a computational method is used where the value of 'v' is chosen so that the DCM and CIMS give converging predictions over a wide range of scenarios.

This second method is advantageous because it does not require programming changes in CIMS. Further, because this project and other concurrent projects only seek to explain some of the equipment choices in CIMS, there will be many nodes where DCM's have not been estimated. Keeping the current algorithm allows avoids having two different choice algorithms embedded in the model.

The two options for using DCM's to improve CIMS are thoroughly discussed in Horne and Rivers (2002). While the first method described was found to be more desirable from a theoretical standpoint, time and resource constraints necessitated using the second method. Consequently, this paper proceeds by estimating behavioural parameters for CIMS based on the DCM. Table 13 gives estimates of the CIMS parameters based on the above equations for the maximum likelihood estimators of the DCM.

**Table 13 - CIMS parameters estimated from the DCM**

<b>Parameter</b>	<b>Value</b>
Discount Rate (r)	34.7
Intangible Costs (i)	
Standard Efficiency Boiler	\$500,000
High Efficiency Boiler	-\$137,000
Cogenerator	\$0
Market Heterogeneity (v)	1.4

The discount rate estimated by this survey is 34.7%. Some analysts suggest that such observed high discount rates on energy investments 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 by the same factor, and exceed the inflated 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 are likely a reflection of the reality of the cost of obtaining information in the market, the difficulties of collective action within a firm, the high perceived risk of energy efficiency investments, the scepticism of company decision makers to *ex ante* claims of high rates of return of energy efficiency investments, the option value of waiting for more information before making a decision, and the limited time available by top decision makers to evaluate energy saving alternatives, among other factors (Harris et al. 2000; DeCanio 1993; Sassone and Martucci 1984; de Groot et al. 2001; Dixit and Pindyck 1994; Hasset and Metcalf 1994). The discount rate calculated in this study is consistent with this latter stream of literature.

The intangible costs of the three technologies are directly proportional to the alternative specific constants in the DCM, and again show that high efficiency boilers are the most preferred technology, followed by cogenerators and then standard efficiency boilers, *ceteris paribus*. These systematic preferences are more important to small firms than to large firms.

The market heterogeneity ('v') factor of 1.4 is low compared to the value currently assumed in CIMS – 10 throughout the industrial sector (refer to Figure 2 for a graphical

interpretation of the 'v' parameter). The low value implies that the market is actually quite heterogeneous, and that investments appropriate for one firm might not be appropriate for another<sup>63</sup>. Throughout the CIMS model, a market heterogeneity factor of between 6 and 10 is normally used, with these values originating from discussions with industry representatives and anecdotal market survey data (Nyboer 1997). The empirical research in this paper shows that it is probably appropriate to use a lower value for the 'v' parameter than is currently used, reflecting a greater degree of heterogeneity than was previously thought appropriate. However, for emphasis I repeat that the value of 'v' calculated in this study is only appropriate in the context of the other parameters estimated from the DCM, and could lead to misleading cost estimates if applied throughout the model in the context of different technology choices. Ideally, future research would be aimed at empirically isolating the true market heterogeneity for a range of technology choices. However, in the interim, the statistical analysis of this study as well as qualitative observation of the survey results suggests that a lower value of 'v' than is currently used in the model would be appropriate for the industrial sector.

Figure 21 shows a schematic representation of the current CIMS steam generation node. According to this structure, a firm requiring steam begins by making a decision of whether to use a boiler or a cogeneration system. With this decision made, the firm then compares the different types of fuel available to generate steam. In this study, however, respondents were assumed to first make a decision about what type of fuel to use, after which respondents were asked to choose between standard and high efficiency boilers and cogenerators as in Figure 22. This formulation fits better with practical constraints in industry, as fuel type is usually more fixed than specific types of technology in use. However, both Figures are equivalent representations of the steam generating technology choice, with Figure 22 simply meshing better with the methodology used in this survey. Accordingly, the structure of the CIMS steam node was changed to reflect Figure 22.

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<sup>63</sup> Because of the previously mentioned difficulty in isolating the 'v' parameter from the DCM, this calculated 'v' is only appropriate in the context of the other calculated CIMS parameters.

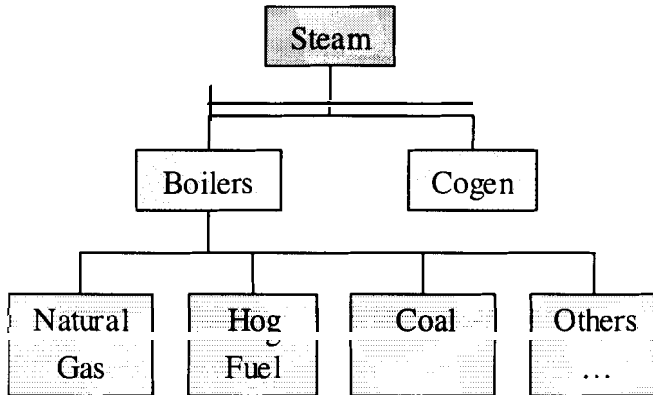


Figure 21 - Current CIMS steam node hierarchy

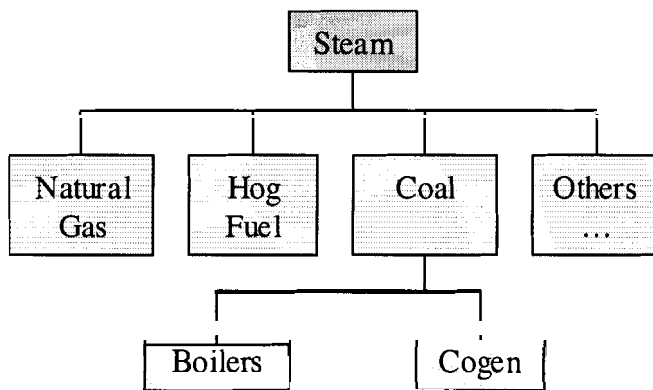


Figure 22 - New CIMS steam node hierarchy

## Policy analysis using CIMS

With the parameters and the structure of CIMS updated to reflect the DCM, it is possible to use CIMS to conduct an integrated, behaviourally realistic, technologically explicit policy analysis on steam generation technologies. Based on the discussion of cogeneration policy options presented throughout this paper, three hypothetical policies were selected for modelling in CIMS:

- **Capital cost subsidy** on cogeneration technologies – a subsidy of 20% of the capital cost of all cogeneration systems was provided to encourage cogeneration.
- **Tax on carbon dioxide** emissions – a \$50/tonnes CO<sub>2e</sub> tax was applied to reduce GHG emissions. Such a policy will increase the amount of cogeneration because

the overall emissions of cogeneration are generally lower than for separate production of heat and power.

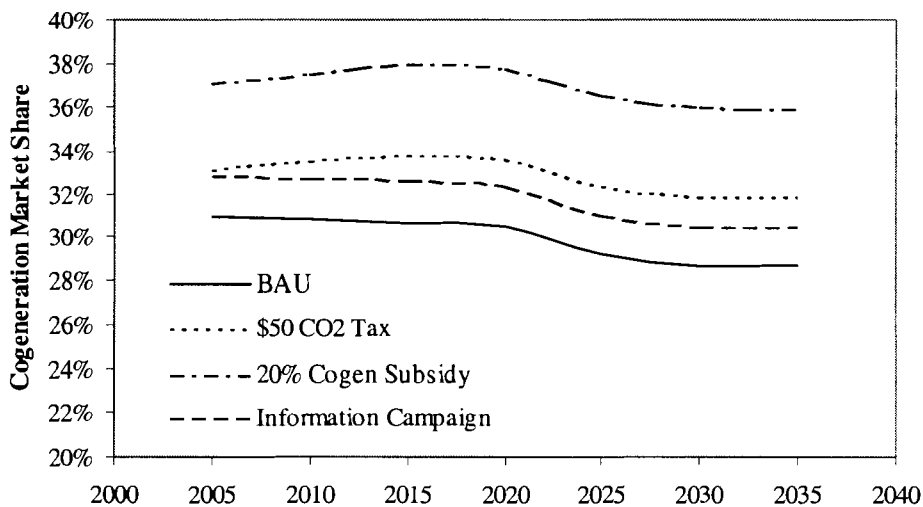
- **Information provision** to diffuse knowledge of cogeneration – an information campaign was initiated to raise knowledge of cogeneration to the level of the respondents who indicated they were “well-informed” about cogeneration.

The results of the policy modelling are given in Figure 23, which shows the evolution in the market share of cogeneration in Ontario over time under different policy scenarios<sup>64</sup>. As expected, with no policy in place (business as usual – BAU), the new market share of cogeneration is low. Information provision increases the new market share of cogeneration by about 2% over business as usual, while the \$50/tonne of CO<sub>2e</sub> tax increases the new market share of cogeneration by 2.5-4% over business as usual. The subsidy has the largest effect on the new market share of cogeneration, increasing it by 6-8% over business as usual<sup>65</sup>. These predictions follow from the elasticity estimates presented in Table 11, which showed that changes to the capital cost had relatively more influence on the market share of steam generating technologies than changes to annual operating costs.

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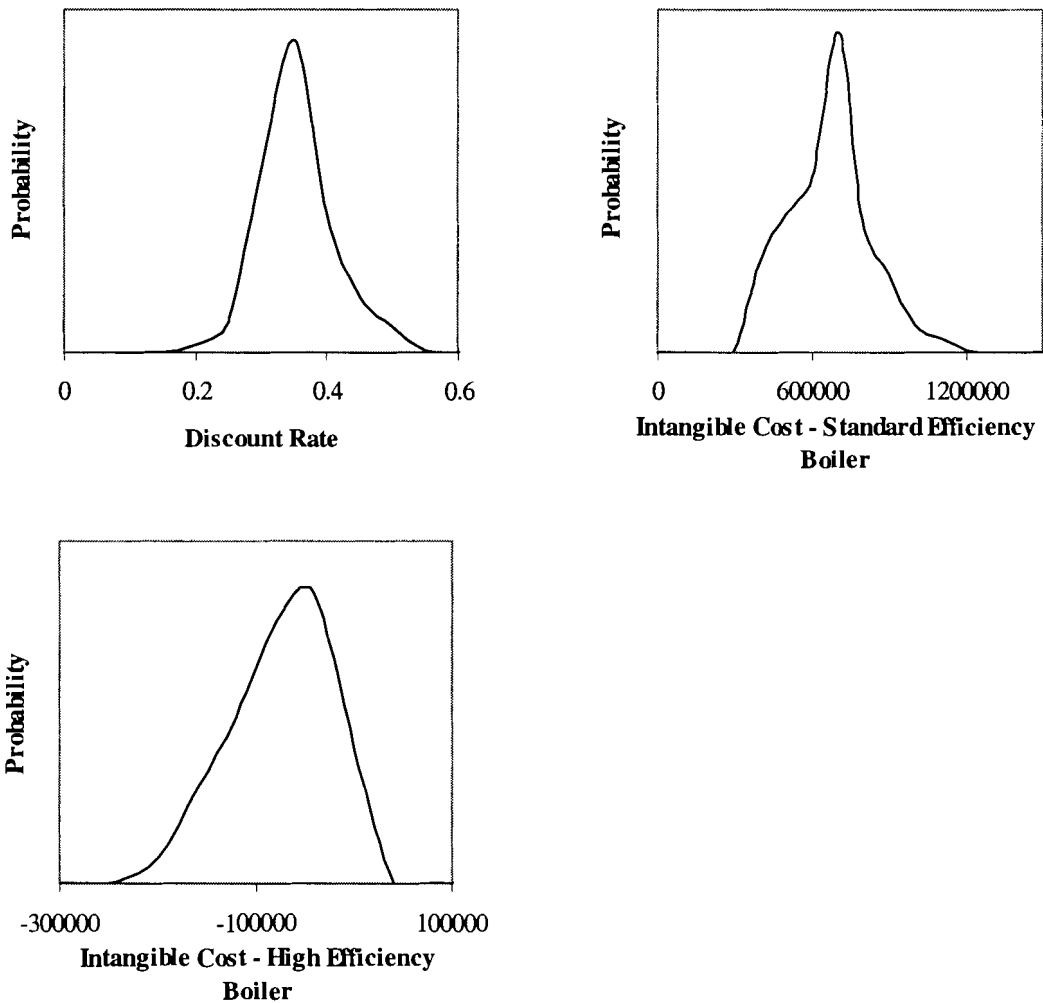
<sup>64</sup> In CIMS, the market share of cogeneration is based on the percentage of total steam in the economy generated through cogeneration, not on the ratio of cogeneration units to boilers in the economy. In the DCM, the market share of cogeneration is based on the ratio of boilers to cogeneration units in the economy. Provided limited bias exists in the survey, the two should map each other closely.

<sup>65</sup> In all scenarios, the market share of cogeneration declines after 2020. This is because of a projected decline in the price of electricity in Ontario after 2020.



**Figure 23 - Effect of cogeneration promotion policies in Ontario**

The preceding CIMS policy analysis was conducted assuming all behavioural parameters estimated from the DCM had no uncertainty associated with them. In reality, as discussed earlier in this chapter, the parameters in Table 9 are only the most likely parameter estimates based on the data. However, there are many other parameter values that are also possible, albeit with less probability. Figure 24 shows the marginal probability distributions for the discount rate and both of the alternative specific constants, which were estimated using a similar procedure as discussed above. These are *marginal* probability distributions because each parameter is not estimated independently of the others. To maintain all information, uncertainty in the CIMS parameters should be shown as a four-dimensional joint probability distribution in which the value of any one parameter depends on the value taken by the other three parameters. Uncertainty estimates are not available for the ‘v’ parameter because it is not estimated directly from the DCM. Instead, an iterative solving procedure is used to assign ‘v’ once all other parameters have been estimated. Because of the large number of calculations required to produce the probability distributions in Figure 24, generating a probability distribution for ‘v’ was not possible. Consequently, the results from the uncertainty analysis will show slightly more confidence than appropriate.



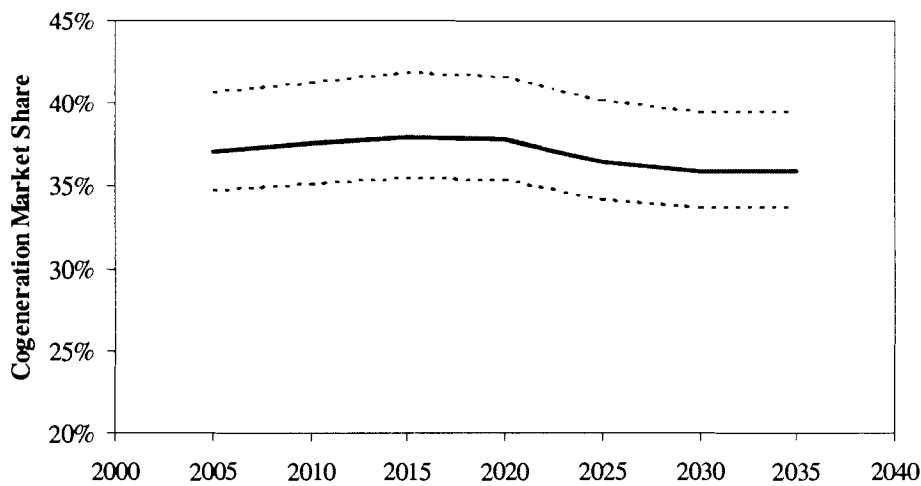
**Figure 24 - Uncertainty in CIMS parameter estimates**

To propagate the uncertainty in CIMS parameters through the model, some method of sampling from the joint probability distribution representing uncertainty in the behavioural parameters should be used. However, even efficient sampling techniques such as Latin Hypercube Sampling require a large number of samples to be drawn from a probability density function to arrive at estimates of uncertainty in model output (on the order of a hundred to a thousand samples). Because of the time required to generate output in CIMS, propagating uncertainty through sampling is not feasible.

Instead, an approximation method is used to estimate the uncertainty in model results due to uncertainty in the behavioural parameters. In this method, output is generated based on parameter values one standard deviation above and one standard deviation below mean attribute values in the marginal probability distributions (corresponding to the 95% confidence interval). Figure 25 shows the results of the simulation of the 20% subsidy on the capital cost of cogeneration with 95% confidence levels. The 95% confidence level corresponds to about an absolute 5-7% deviation in the market share of cogeneration.

While this method of estimating the uncertainty is attractive because of its simplicity, it is actually only a crude approximation of the uncertainty in the results due to the parameter uncertainty. It is theoretically unsound to equate the 95% confidence interval on each of the three parameter distributions with the 95% confidence interval in the outcome. This is because the distributions around the three CIMS parameters shown are marginal distributions, meaning that they are not independent from each other. Treating them as independent (as has been done here) is incorrect, but was necessary to make the problem tractable. Further, the calculation shown here makes the tenuous assumption that there is a direct translation between the confidence intervals in the input parameters and in the output. Ideally, as mentioned above, some sampling method would have been used to estimate uncertainty in the outcome, however, the time requirements of CIMS rendered that option infeasible.





**Figure 25 - Uncertainty in CIMS output**

It is important to recognize that the uncertainty portrayed in Figure 25 does not fully represent the uncertainty associated with this modelling exercise. Actually, it only represents the uncertainty associated with the behavioural parameter estimates *given* that the data set is a perfect representation of firm behaviour. Of course, the data set does not fully represent firm behaviour, 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 results of the survey questions, or do not answer the questions truthfully.

Further, uncertainty exists not only in the representation of behaviour, but also in the representation of technology. Costs for the various steam generating technologies were assessed several years ago for CIMS and cannot be taken to be fully up to date today. As

well, all cogeneration technologies in the database are bottom-cycle steam turbines, while in reality a large portion of the new cogeneration facilities in Canada are topping-cycle gas turbines and combined cycle gas turbines. Also, although cogeneration in Canada is constrained in part due to unwillingness on the part of electric utilities to accept excess cogenerated electricity, in CIMS as currently calculated all electricity generated by a cogeneration facility is worth the full value of electricity purchased from the utility.

Because of the combination of these errors, the confidence intervals presented in Figure 25 should be taken as an absolute lower bound on the amount of uncertainty actually present in this exercise.

## **Informing NEMS with the DCM**

Every year the Energy Information Administration (EIA) of the US Government releases an Annual Energy Outlook (AEO) that projects energy supply, demand, prices, and emissions in the US for the coming 20-25 years. To produce the AEO, the EIA has developed and employs a hybrid energy-economy model called the National Energy Modelling System (NEMS), which tracks fuel prices and technology evolution throughout the US economy. In addition to its role in producing the AEO, NEMS is used to forecast the effects of policy initiatives on the economy (EIA 2003)<sup>66</sup>. Because of the prominent role of NEMS in the energy-economy modelling community, this section discusses how the results from this research could be used in NEMS.

The Industrial Demand Module of the NEMS model calculates the consumption of energy in the industrial sector based on assumptions about fuel prices, employment, and industry structure. The module is broken up into fifteen industry groups in energy-intensive and non-energy intensive manufacturing sectors and in the non-manufacturing sector. Within each group, energy demand is separated into three interrelated components: building energy consumption, process and assembly energy consumption, and

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<sup>66</sup> In this sense, NEMS is designed for a similar purpose as the CIMS model.

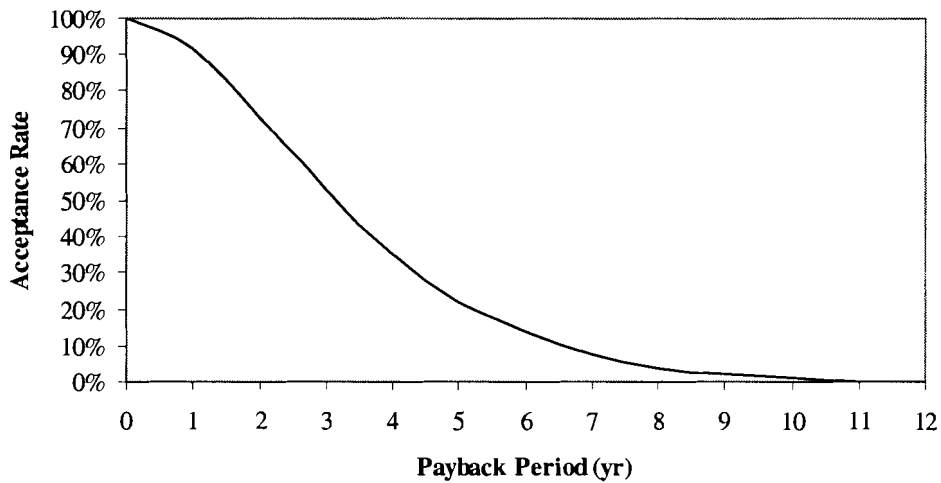
boilers/steam/cogeneration energy consumption. The boiler/steam/cogeneration component satisfies the steam demand from the other two components. Like CIMS, NEMS is a technology vintage model, meaning that it tracks the evolution of technology stocks through retirements, retrofits, and new purchases.

The NEMS model methodology for determining the penetration of industrial cogeneration is as follows (EIA 2003). First, the technical potential for cogeneration is calculated under the assumption that all non-cogenerated steam in industry is converted to cogeneration. Second, the payback for each hypothetical conversion from a boiler to a cogeneration system is calculated, based on assumptions about the current boiler stock and economic assumptions about cogeneration systems<sup>67</sup>. Third, the fraction of technical cogeneration potential that is considered economical is calculated using the payback acceptance curve shown in Figure 26. The curve shows the fraction of industrial firms that would convert to cogeneration for a given payback period<sup>68</sup>. The curve shows that all investments with a zero-year payback are made, while only 13.5% of those with a six-year payback are made, for example. Finally, the annual capacity additions are calculated from the assumption that all the economic potential will be realized over a 20 year horizon, so in one year, 5% of the total economic potential of cogeneration will penetrate. These calculations are repeated for every year of the analysis.

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<sup>67</sup> The assumptions regarding the costs of cogeneration systems of various specifications used in the NEMS model are given in Table B20 of *NEMS Industrial Model Documentation Report 2003*.

<sup>68</sup> The payback acceptance curves used in NEMS are calculated using a combination of empirical evidence and judgment. Empirical evidence to construct the curves came from a report by the Energy Analysis and Diagnostics Centre (EADC) of the US Government that synthesized results from a large number of projects in industry (including their payback period) and listed whether or not they had been undertaken (Honeycutt 2003).

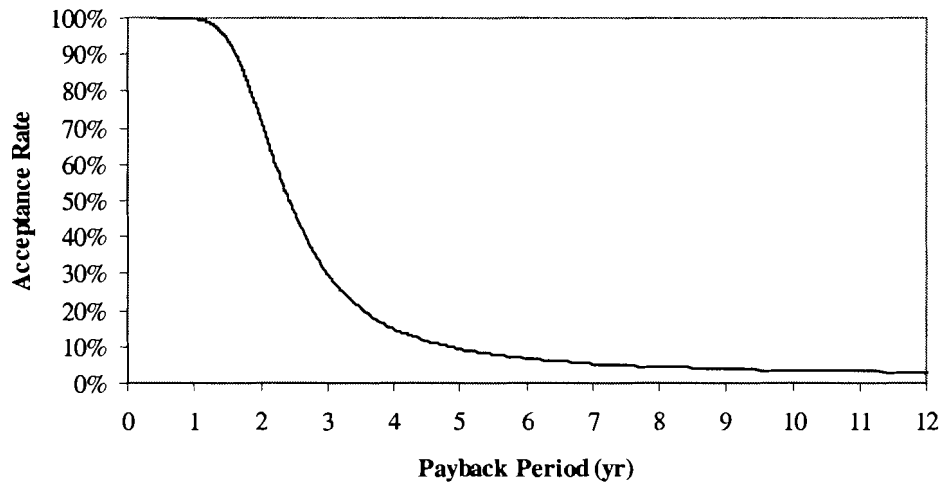


**Figure 26 - NEMS cogeneration payback acceptance curve**

While the methodology described above is significantly different than the methodology used in CIMS or the discrete choice model for forecasting the evolution of steam generation technologies, there is potential that this study could be used to inform the calculation of the economic potential of cogeneration in NEMS. The economic potential in NEMS is based on the payback acceptance curve, which synthesizes information on firm discount rate (the ‘r’ parameter in CIMS) with information on heterogeneity in the market (the ‘v’ parameter in CIMS). Missing from the calculation of the economic potential in NEMS is any notion that industrial consumers might have non-monetary preferences for the different technologies able to meet their steam demand (the ‘i’ parameter in CIMS). These intangible costs have been calculated in this study (see table 12), and should be able to be adopted by NEMS in a similar way to CIMS (by directly adding them on to the annual costs).

A payback acceptance curve was calculated from the results of this study by using the discrete choice model to estimate the market share of cogeneration that would be chosen given different assumptions about economic conditions (payback). This curve is shown in Figure 27. This curve would need to be calculated separately for different size classes, as it changes shape depending on the size of the incremental investment and savings

offered through the adoption of a cogeneration system (i.e., the scale of the cogeneration system being considered).



**Figure 27 – Sample payback acceptance curve derived from this study**

Using a payback acceptance curve similar to Figure 27 and the intangible technology cost information makes the results of this study applicable to NEMS, a hybrid model with a similar purpose, but different design, than CIMS.

## 5. Conclusions

The objective of the research described in this paper was to use a discrete choice model, a proven and effective method for understanding the decision making process of an economic agent, to characterize the industrial steam generation decision, and thereby provide a firmer empirical foundation for the behavioural parameters of an integrated energy-economy hybrid model. The hybrid model was then used to account for energy system feedbacks that occur as a result of one or several energy-environment policies. Looking over the completed exercise, it is possible to evaluate its usefulness in meeting the stated objective and to propose extensions that would be useful in furthering this stream of knowledge. The following conclusions are separated into conclusions pertaining to improving economic models, and conclusions regarding industrial decision making with respect to steam generating technologies, particularly cogeneration.

### 5.1 Cogeneration

This study used industrial cogeneration as a case study to explore the validity of using discrete choice models to estimate the behavioural parameters in a hybrid energy-economy model. While the following section deals with conclusions relating to the methodology used, this section deals with the results of the study.

The discrete choice model was estimated from stated preference survey results from 259 plant managers in industry, each of whom answered 4 choice questions. The discrete choice model estimated from the data set had all coefficients of the correct sign, and all coefficients significant at the 90% confidence level, save the operating cost coefficient<sup>69</sup>. The alternative specific constants estimated show that high efficiency boilers are the most preferred technology, followed by cogeneration, *ceteris paribus*. These technology-

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<sup>69</sup> It showed that increases in capital, operating, or fuel costs or decreases in electricity savings decreased the likelihood of an alternative being chosen.

specific preferences are more important to firms using a small amount of steam than to large consumers of steam.

Elasticity estimates were made from the model, which show the predicted change in market share based on a change in attribute levels. The elasticity estimates reveal two important conclusions relating to steam generation technology decision-making.

First, the elasticities calculated from the survey results show that manipulating the capital cost through policy is a much more effective way to shape steam generating technology adoption than manipulating the annual costs. This study showed that a \$1,000,000 subsidy on the capital cost of a cogeneration system would increase the adoption of cogeneration over nine times as much as the same sized subsidy on the fuel or operating cost<sup>70</sup>. As a result, any subsidy aimed at increasing the adoption of cogeneration in Canada should target the capital cost of a cogeneration system, rather than the operating or fuel costs, for maximum effectiveness.

Second, the electricity savings from a cogeneration system are valued very highly by industrial firms. When a firm is able to produce its own electricity, it insulates itself somewhat from disturbances to the electricity grid. In so doing, it can dramatically increase the reliability of its electricity supply and decrease its exposure to financial risk, both of which are valued extremely highly by firms. Consequently, increases in the price of electricity (or in some cases increases in firms' perceptions of uncertainty regarding the future price of electricity) could be expected to increase the attractiveness of cogeneration to industry. Because the electric utility governs the price of electricity bought and sold between the electric utility and the firm, a major point of leverage for increasing the penetration of cogeneration is through regulating the relationship between electric utilities and cogenerators. Legislation governing this relationship exists in many countries, and has often proven effective in increasing the penetration of cogeneration. In the US for example, the Public Utilities Regulatory Policy Act was enacted in 1978 and

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<sup>70</sup> Assuming a 10% social discount rate.

increased the penetration of cogeneration by a factor of four over the course of a decade (Dismukes and Kleit 1999; Cudahy 1995).

The discrete choice model was subsequently integrated into CIMS, a hybrid model of the Canadian energy economy, by estimating parameters that characterize the discrete choice results in a manner useable by CIMS. This process revealed that a discount rate of 34.7% can be used to explain the decisions made by industrial plant managers. Such a discount rate, while seemingly high, is consistent with the literature and likely reflects decision making under uncertainty, risk aversion, and option value, as well as information problems, collective action failures, and resource and time constraints. The process also suggests that the industrial sector is extremely heterogeneous, with decisions and technologies appropriate for one plant not necessarily appropriate for another.

With the information from the discrete choice model embedded in CIMS, a policy analysis was conducted to measure the effect that various policy instruments would have on the penetration of cogeneration. The results reveal that a well-designed information campaign targeted at plant managers with little current knowledge of cogeneration could raise the new market share of cogeneration by about 2% over business as usual. A \$50/tonne of CO<sub>2e</sub> would raise the new market share of cogeneration by 2.5-4% over business as usual, while a 20% subsidy on the capital cost of cogeneration would increase its new market share by 6-8% over business as usual. A quantitative uncertainty analysis showed that the results are probably correct to within plus or minus 2.5-3.5% at the 95% confidence level<sup>71</sup>.

The survey also revealed that there is a systematic lack of knowledge and familiarity with cogeneration throughout Canadian industry. Only 34.6% of plant managers surveyed reported knowing of a cogeneration system operated by any plant in their industrial sector. Even less reported being “very well informed” or “well informed” about important technical, financial, and regulatory issues surrounding cogeneration.

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<sup>71</sup> All percentages listed in the paragraph refer to absolute market share changes, not to relative percentages.



Particularly telling is the fact that only about one quarter of the respondents indicated that their plant had even considered using a cogeneration system in the past – meaning that 75% of plants chose a boiler over a cogeneration system based not upon the relative merits of each technology, but based instead on lack of information about cogeneration systems. Lack of information in the market is considered a market failure by some economists and can merit correction by public policy (Jaffe and Stavins 1994b). Cogeneration demonstration projects and increased cogeneration exposure at trade shows or promotion by industrial sector trade groups could be useful tools for raising awareness of cogeneration.

## ***5.2 Modelling***

In any paper based on the results of an economic modelling exercise, a discussion of the validity of such models should occupy a conspicuous position where any potential reader can be sure not to miss it. Economic models make predictions about future human behaviour, based on explicit or implicit observations of past human behaviour. In so doing, they are borrowing a page from the book of the natural sciences, where laws of nature observed in the past can be reliably forecast into the future to make predictions. However, as Koomey (2002) points out, the laws of nature are immutable – they are predictable and do not change over time. For example, I can be sure that if I push a block of metal over a frictionless surface, it will accelerate at a rate given by the ratio of the force of my push to the mass of the block. There exists no such guarantee of stasis in human behaviour however. My observation that most people in North America exhibit a systematic preference for driving oversized sport utility vehicles to work today, for example, is no guarantee that the same preference will hold in twenty years. In fact, when attempting to predict the evolution of the economic system over a time span of twenty years or greater, we can be virtually guaranteed that unpredictable changes in human preferences and behaviour will lead to errors in our predictions. As a result, any time we model the economic system to make predictions about the future, we are almost certain to get the answer wrong.

Am I implying that this entire exercise in attempting to quantitatively understand human behaviour has been futile? Far from it; in fact, I think research in this vein is critical if we are to design effective policies aimed towards sustainability. Policy makers and analysts turn to economic models because they are often the best (and only) tools available for predicting the effects of policies. Without economic models, policy makers would be left with the same set of initial assumptions and the same historical data sets, but with no unifying framework to structure those assumptions. Economic models provide that framework, and additionally enable the policy maker or analyst to predict how alternative assumptions about human behaviour would change the forecasts. Despite the inherent uncertainty in their results, economic models can be useful tools for policy makers.

Our challenge, laid out in this way, is to design an economic model that is useful to policy makers and analysts. Previous generations of models – traditional bottom-up and top-down models – have fundamental theoretical weaknesses that limit 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 dubious assumptions about human behaviour, with the result that their predictions are unrepresentative of the economic system. Because of the fundamental theoretical weaknesses of previous generations of models, a new generation of economic models has emerged that incorporates the strengths of both bottom-up and top-down models. These hybrid models contain both an explicit representation of the technologies in the economic system and a representation of behaviour based on real market behaviour. A ‘true’ hybrid model is based on a complete database of the technologies in the energy 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 real 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 behaviourally realistic and technologically explicit.

The approach taken in this paper has been to develop a discrete choice model and use it to improve the behavioural realism of a hybrid model. While it has been a fruitful process, there are obviously some lessons learned that could be used to improve future research:

- Revealed preference data could be a useful supplement to stated preference data;
- Preferences are dynamic, not static, and should be treated as such; and,
- Many extensions of the simple multinomial logit model exist that could lend more credence to the analysis of the data.

Each of these topics is discussed in detail in the following pages.

### **Combined preference data**

All stated preference surveys suffer from the flaw that they do not necessarily reflect the choices and preferences of a respondent in the real world. Although stated choice experiments are designed to mimic real choice situations that would be faced by a respondent as much as possible, in the choice experiment respondents are not constrained by information or financial barriers as in the real world, and can even answer choice experiments consciously wrongly in order to bias survey responses or satisfy the analyst (Train 2002). This survey suffered from the additional problem that it was difficult to identify the appropriate person in the firm to survey. The plant manager was identified as the most likely person in the plant to be involved in the steam generation technology decision; however, in reality decisions on this financial scale are likely undertaken by several people within the firm. Outcomes from a multi-person taskforce with substantial time for decision-making could diverge from the answers on the survey. Raising further problems with this survey is that steam-generating technologies have lifetimes of over 25 years – often longer than a plant manager’s career. Because of this, at least some of the plant managers in the survey likely have had no experience with the purchase of boilers or cogenerators before completing the choice experiment.

Revealed preference data overcome many of these problems but have a suite of problems of their own. In particular, they often do not contain the needed variation in data for

estimating a model, the data streams are correlated, and they are not useful for probing the effects of policies that diverge from past experience.

Advantages can be gained by combining revealed preference data and stated preference data in order to take advantage of the strengths of each type of data source. While this was beyond the scope of the paper, it is instructive to briefly mention the process for combining the two forms of data. The advantage of stated preference data is that it provides the needed attribute variation to estimate a discrete choice model, while the advantage of revealed preference data is that it reflects reality (i.e., the market shares predicted by the model will be the same as reality). To combine these strengths, Ben Akiva and Morikawa (1990) and Hensher et al. (1999) describe a process whereby the ratios of coefficients are estimated from stated preference data, while the overall scale of the model (equivalent to the 'v' parameter in CIMS) and the alternative specific constants are estimated from revealed preference data. This method is still in its early stages of development, yet shows promise for improving the quality of discrete choice analysis. Further work in the vein of this study would likely benefit from the use of combined preference data.

### **Static vs. dynamic modelling**

Dynamics in preferences and learning are currently the subject of much research by the energy-economy modelling community. While the conventional assumption in economic modelling is that preferences can be accepted as given and stable for the purposes and duration of the economic study, an abundance of research shows that consumers change their preferences in response to external stimuli (Norton et al. 1998). For example, preferences are likely influenced by the physical environment (e.g., widespread evidence of global warming could lead some firms to adopt more energy efficient technologies), the social environment (e.g., firms could be influenced by the type of technology adopted by other neighbouring or competing firms, as well as broader social pressure) or the political environment (e.g., research has shown that there is an 'announcement effect' for policies that can actually trigger more change than the policy itself (Koomey 2002)).

Since there is significant evidence that preferences do actually evolve in the face of a changing external environment, incorporating preference dynamics into energy-economy models is an important step for improving the behavioural realism of such models.

The CIMS model attempts to partially capture preference dynamics caused by changes in the social environment. For emerging technologies in CIMS (e.g., hybrid or fuel cell cars, wind turbines, and solar photovoltaic power) the intangible cost ('i' parameter) is a function of the technology's market share. As the market share of the emerging technology increases, it is assumed that increased familiarity with the technology acts to increase the attractiveness of the technology to consumers (through, for example, lowering the risk of adopting the technology or through increasing the amount of information readily available regarding the technology – see McFadden and Train 1996). The CIMS parameter reflecting this changing preference for new technologies is set primarily through judgement<sup>72</sup>.

CIMS also models learning dynamics in technology adoption that directly affect the financial costs of technologies, rather than their intangible costs. Analysis suggests that there is a learning-by-doing effect whereby producers gain expertise with increased manufacturing experience. This accumulated expertise drives down costs (see, for example, Ibenholt 2002, for learning curves in wind turbines). CIMS incorporates learning-by-doing effects for many emerging technologies, with learning curve parameters set from the literature<sup>73</sup>.

To be most useful, this study would have attempted to estimate, through rigorous empirical methods, parameters reflecting social, political, as well as environmental

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<sup>72</sup> It is set equal to the technology learning parameter, discussed in the following paragraph. I refer to this as "judgement" because a rigorous empirical basis does not exist for assuming that the two parameters should have the same value.

<sup>73</sup> Learning effects in CIMS, however, are based on a technology's current market share, while theory and the literature use cumulative technology production to estimate cost reductions through learning effects. While the two are related, the use of market share to estimate cost declines in CIMS can lead to incorrect estimation of learning effects in some cases.

preference dynamics in the steam generating technology choice (this study was not appropriate for estimating the parameters in an experience or learning curve, and many other studies focus on estimating this parameter). This study, however, instead focused on estimating a model in which preferences are fixed through time<sup>74</sup> for the adoption of steam generating technologies, for two reasons. First, I felt that the choice experiment, as administered, was complex enough without the introduction of other confounding factors. Accumulated experience with surveys discussed in the literature has found that respondents have a limited ability (and patience) for analyzing complex choice experiments (Louviere et al. 2000). Second, it is unclear whether a stated choice experiment is suitable for capturing preference dynamics. Stated choice experiments are most useful when they closely replicate real experiences of the respondents. When they ask respondents to put themselves in situations that are not similar to their experiences, they are likely to produce erroneous modelling results<sup>75</sup>. Because of this, the use of stated preference techniques to elicit preference dynamics parameters could actually introduce a higher degree of uncertainty into energy-economy models than would be there in the absence of such parameters or through using judgement to estimate parameter values. Future research aimed at capturing these parameters through rigorous empirical techniques should consequently probably be strongly based on revealed preferences, possibly in combination with stated preferences. In the interim, the CIMS model is able to simulate both learning-by-doing and social preference dynamics using parameters set primarily through judgement and meta-analysis. The analyst is able to test various assumptions about the rate of learning and preference shift and base policy recommendations on most likely estimates for these parameters.

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<sup>74</sup> Even in the discrete choice model estimated in this study, there are elements that would be referred to as dynamic by most economists. A change in prices, for example, results in a change in technology adoption in the discrete choice model. Similarly, the provision of information to firms is predicted to affect the market share of the technologies being modeled.

<sup>75</sup> For example, Urban et al. (1996) attempt to hypothetically put respondents several years into the future and measure preferences for new electric vehicles. They find that the experiment significantly overestimates the real probability of electric vehicle purchase due to its hypothetical nature. They correct their forecasts using revealed preference data.

## **Advanced discrete choice methods**

Early in the development of discrete choice models, lack of computing power constrained researchers to assume a simple, closed form for the distribution of the unobserved portion of the utility function (the error), and to assume that these errors were independent of one another. The result was the development and widespread application of the multinomial logit (MNL) model based on the type I extreme value distribution for the error term (which was also used in this paper). More recently, however, researchers have developed an array of alternative, less restrictive, assumptions about the distribution and correlation of the error term, which modern computing techniques can help solve. A brief description of some of the main alternatives to MNL follows from Train (2002).

Generalized extreme value (GEV) models relax the assumption that the error term for each alternative is independently distributed. Instead, they propose a model where the error terms can be correlated, resulting in a model with more complex substitution patterns than a simple MNL model. The conventional application of GEV models is nested logit models, in which the available alternatives are grouped into ‘nests’ to better replicate the consumer’s decision process. In this research for example, a possible nested logit model would see both standard and high efficiency boilers in one nest, and cogeneration systems in another. If the plant managers in the survey actually made choices in this way (i.e., choose between boiler and cogenerator first, and then if a boiler is chosen, choose between standard efficiency and high efficiency), a nested logit model would fit the data better than the MNL.

Probit models also relax the assumption that the error term for each alternative is independently distributed, and additionally, they allow for random taste variation in the population. Allowing random taste variation amounts to assuming that coefficients in the discrete choice model can be represented as distributions, rather than fixed values. In this way, it is possible for one plant manager to exhibit a different preference for high efficiency boilers than another in the sample, and to capture that difference using a distribution, rather than using a point somewhere between the two (as is done in an MNL model). This extra flexibility means that probit models usually fit a data set better than

MNL models. Probit models are restricted, however, because they require the assumption that the distribution of random taste variation within the population is normally distributed. While this is often a valid assumption, there are cases where it might not be.

Mixed logit models offer an alternative to probit models that do not require any forced assumptions about the distribution of the error terms. This flexibility is paid for, however, because mixed logit models cannot be directly solved through analytical techniques, instead requiring time consuming computational solutions. Because of this, it is only in the past few years that mixed logit models have been applied, but early indications show that the extreme flexibility of this functional form will lend more strength to discrete choice models in the future.

Clearly, there are many alternatives to the MNL that are likely to improve the quality of the models developed. Further research aimed at strengthening hybrid energy-economy models through the application of discrete choice techniques will eventually have to consider these advanced methods.

## **Summary**

Despite the limitations of the study, this paper shows that empirical observation and analysis of consumers' choice of technology can improve the realism of hybrid models. Discrete choice methods are only one method of conducting such analysis, but are well suited for integration into an energy-economic framework that captures feedbacks throughout the economy. In addition to lending more credence to modelling results, the empirical nature of this method enables the analysis of model uncertainty. Such an analysis is useful not only because it clearly expresses the confidence in the model results, but also because it allows results to be objectively compared between models.

Although this study successfully demonstrated the potential for empirically estimating the parameters of a hybrid model, work remains before such a model can be considered complete. Probably the most important indication that points towards the requirement for



future research is that the baseline predictions for technology adoption in this study diverge significantly from reality – in this study, cogeneration is predicted to be chosen by 27% of firms in the sample, while it is only chosen by about 9% of firms in reality (in the industrial sectors considered in this study). While it is possible that this divergence reflects the true market potential of cogeneration, in all likelihood, it also reflects the limitations of this study and the CIMS model. In particular, further work aimed at:

- Combining stated and revealed preferences,
- Using more sophisticated discrete choice methods,
- Improving the representation of steam generating technologies and the quality of the technology data in CIMS, and
- Estimating discrete choice models based on a more complete utility function (that better accounts for non-financial costs)

could be expected to produce a more valid and behaviourally realistic model than the one discussed in this paper. However, it needs to be made clear that this study, while far from perfect or complete, offers a significant improvement for the representation of industrial behaviour in hybrid models.

In summary, this paper shows that empirically gathering information on consumers' technology choices to inform a hybrid model is a useful and credible method for modelling policies in the energy sector. Further research in this field could be expected to further increase the realism of hybrid models.

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## Appendix 1 – Ethical approval

# SIMON FRASER UNIVERSITY

OFFICE OF RESEARCH ETHICS



BURNABY, BRITISH COLUMBIA  
CANADA V5A 1S6  
Telephone: 604-291-3447  
FAX: 604-268-6785

May 12, 2003

Mr. Nicholas Rivers  
Graduate Student  
School of Resource and  
Environmental Management  
Simon Fraser University

Dear Mr. Rivers:

**Re: Industrial Heating Technology Survey**  
*NSERC, Office of Energy Efficiency (Government of Canada)*

The above-titled ethics application has been granted approval by the Simon Fraser Research Ethics Board, in accordance with Policy R 20.01, "Ethics Review of Research Involving Human Subjects".

Sincerely,

Dr. Hal Weinberg, Director  
Office of Research Ethics

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\* For inclusion in thesis/dissertation/extended essays/research project report, as submitted to the university library in fulfillment of final requirements for graduation. Note: correct page number required.

## Appendix 2 – Telephone survey script

### Legend

*Instructions are in italics.*

Script is in normal font.

Categories for answers are in boxed text.

### Survey Script

→ A. *Call main contact number for company.*

Hello, my name is [...] and I'm calling on behalf of researchers at the Energy and Materials Research Group of Simon Fraser University. Could you provide me with the name and telephone number of the plant manager at your facility?

→ B. *Record name and telephone number of plant manager.*

→ C. *Call plant manager.*

Hello, my name is [...] and I'm calling on behalf of researchers at the Energy and Materials Research Group of Simon Fraser University who are conducting a survey of boilers and cogeneration systems in industry. Would you be willing to participate in a telephone survey that will take less than five minutes of your time and a brief follow-up mail survey? All responses will be kept confidential and used only in aggregated form.

→ D. *If they answer NO:*

Can you suggest the name of someone else in your company familiar with your plant operation that might be able to provide us with this important information?

→ D1. If they answer **YES**, start again from (B) with new contact information.

→ D2. If they answer **NO**, terminate interview.

→ E. If they answer **YES**:

I am now going to ask several short questions about your plant's energy consumption. Answer the questions to the best of your ability. All of the information will be kept confidential and will not be tied in any way to you or to your company.

1. Does your plant operate a steam boiler?

- Yes
- No
- Don't Know

→ F. If they answer **YES** to question 1, proceed to question 2. If they answer **NO**, terminate interview. If they answer **DON'T KNOW**, go to (D).

2. What is the approximate steam output of your plant's largest steam boiler? Give your answer in units of pounds per hour of steam.

- Up to 20,000 lb/hr
- Between 20,001 and 50,000 lb/hr
- Between 50,001 and 100,000 lb/hr
- Between 100,001 and 200,000 lb/hr
- Over 200,000 lb/hr
- Don't Know

3. What is the highest output steam pressure from your boilers? Give your answer in units of P.S.I..

- Up to 150 psi
- Between 151 and 500 psi
- Between 501 and 1000 psi
- Over 1000 psi
- Don't Know

4. What is the primary fuel type burned in your boilers?

- Natural Gas
- Oil (Heavy Fuel Oil)
- Coal (Coke)
- Hog Fuel
- Plant Gas/Refinery Gas
- Propane Liquids
- Butane Liquids
- Middle Distillates
- Black Liquor
- Don't Know

5. What percentage, if any, of the fuel burned in your boilers is fuel produced on site?

- None
- Up to 25%
- Between 26 and 50%
- Between 51 and 75%
- Between 76 and 100%

That completes the telephone portion of this survey. So that we can send you the mail section of this survey, can I confirm that the address I have for you is correct:

*Read out address to confirm. If different, record.*

In approximately one week, you will receive the mail portion of this survey, which we anticipate taking less than 15 minutes to complete. As I have explained, your feedback on this survey is very important to us, since it allows us to get an accurate picture of the perspectives of industry on energy using technologies. Please take the time to complete and return the survey upon receiving it. Thank you very much for your time and help in this important project.

### Appendix 3 – Fractional factorial experimental design

Run	SBCC	SBOC	SBFC	HBCC	HBOC	HBFC	COCC	COOC	COFC	COES
1	123%	100%	123%	112%	85%	93%	95%	85%	85%	120%
2	123%	115%	108%	85%	115%	110%	85%	85%	105%	100%
3	100%	115%	100%	98%	115%	102%	90%	100%	115%	100%
4	115%	100%	115%	112%	115%	110%	95%	85%	95%	100%
5	115%	115%	100%	85%	85%	93%	85%	85%	115%	120%
6	108%	100%	108%	85%	115%	102%	85%	85%	95%	120%
7	100%	100%	100%	85%	85%	85%	85%	85%	85%	100%
8	115%	100%	108%	112%	115%	85%	95%	100%	105%	120%
9	115%	115%	115%	125%	85%	93%	100%	100%	105%	100%
10	123%	115%	115%	85%	115%	85%	85%	100%	95%	120%
11	108%	115%	123%	112%	85%	85%	95%	85%	115%	100%
12	123%	115%	123%	125%	115%	110%	100%	100%	115%	120%
13	108%	100%	123%	125%	115%	102%	100%	100%	85%	100%
14	123%	100%	100%	112%	85%	102%	95%	100%	115%	100%
15	123%	100%	115%	98%	85%	102%	90%	85%	105%	120%
16	123%	100%	108%	98%	85%	93%	90%	100%	95%	100%
17	100%	100%	123%	85%	85%	110%	85%	100%	115%	120%
18	108%	115%	115%	98%	85%	110%	90%	85%	95%	100%
19	108%	100%	115%	85%	115%	93%	85%	100%	105%	100%
20	108%	115%	100%	112%	85%	110%	95%	100%	85%	120%
21	115%	100%	100%	98%	115%	110%	90%	100%	85%	120%
22	100%	100%	108%	125%	85%	110%	100%	85%	105%	100%
23	123%	115%	100%	125%	115%	85%	100%	85%	85%	100%
24	100%	100%	115%	125%	85%	85%	100%	100%	95%	120%
25	108%	100%	100%	125%	115%	93%	100%	85%	115%	120%
26	115%	115%	108%	125%	85%	102%	100%	85%	95%	120%
27	100%	115%	123%	98%	115%	93%	90%	85%	85%	120%
28	115%	100%	123%	98%	115%	85%	90%	85%	115%	100%
29	100%	115%	115%	112%	115%	102%	95%	85%	105%	120%
30	100%	115%	108%	112%	115%	93%	95%	100%	95%	100%
31	108%	115%	108%	98%	85%	85%	90%	100%	105%	120%
32	115%	115%	123%	85%	85%	102%	85%	100%	85%	100%

Notes: SBCC refers to the standard efficiency boiler capital cost, SBOC to the standard efficiency boiler operating cost, SBFC to the standard efficiency boiler fuel cost, HBCC to the high efficiency boiler capital cost, and so on.

# INDUSTRIAL HEATING TECHNOLOGY SURVEY

A research project by the

**Energy and Materials Research Group  
School of Resource and Environmental Management  
Simon Fraser University**

Conducted with the financial support of the

**Office of Energy Efficiency  
Natural Resources Canada**

## ***Part A – Energy Use in Your Plant***

1. What is the annual fuel consumption in your plant?
- Throughout the survey, “your plant” refers to the plant at your current location, or if you work with more than one plant, the primary plant with whom you work
  - Include all fuels produced on-site as well as all purchased fuels
  - Use the LHV (lower heating value) of the fuels in the calculation
  - Do not include electricity purchased from the electric utility.
- |   |                  |   |
|---|------------------|---|
| <p><input type="checkbox"/> Less than 100 TJ</p> <p><input type="checkbox"/> 100 – 1,000 TJ</p> <p><input type="checkbox"/> 1,001 – 5,000 TJ</p> <p><input type="checkbox"/> More than 5,000 TJ</p> | <p><u>OR</u></p> | <p><input type="checkbox"/> Less than 100,000 MBTU</p> <p><input type="checkbox"/> 100,000 – 1,000,000 MBTU</p> <p><input type="checkbox"/> 1,000,001 – 5,000,000 MBTU</p> <p><input type="checkbox"/> More than 5,000,000 MBTU</p> |
|---|------------------|---|

2. How much electricity does the plant purchase annually from the electric utility?
- Less than 5,000 MWh
  - 5,000 – 25,000 MWh
  - 25,001 – 100,000 MWh
  - More than 100,000 MWh

<b>Part B – Heating Technologies</b>
--------------------------------------

In this section, you will be asked about your perspective on cogeneration technologies. Cogeneration is the sequential production of heat and electricity from one fuel source. Cogeneration technologies usually have higher capital costs than a standard boiler, but result in reduced electricity costs due to on-site electricity production.

3. Does your plant currently cogenerate heat and electricity on site?
- Yes                    }   ⇒ *If yes, go to question 4*
  - No                        }   ⇒ *If no or don't know, go to question 5*
  - Don't know
4. If your plant does use a cogeneration system, what technology is used?
- Steam turbine
  - Gas turbine
  - Combined cycle gas turbine (CCGT)   ⇒ **Skip to question 6 after answering this question**
  - Reciprocating engine
  - Other (specify)
- 
5. Has your plant ever considered installing a cogeneration system?
- Yes
  - No
  - Don't know
6. Please mark the box that best describes your current state of knowledge of cogeneration technologies in each of the following categories.



	Your knowledge of cogeneration				
	Very well informed	Well informed	Somewhat informed	Not very informed	Uninformed
Engineering developments and technical issues in cogeneration	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Financial issues and costs of cogeneration	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Electric utility or government regulatory developments affecting cogeneration	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

7. Do you know of other plants in your industrial sector (for example, textile manufacturing or pulp and paper) that employ a cogeneration system in their plant?
- Yes
- No

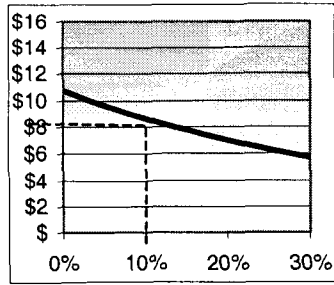
### **Part C – Choice of Heating Technology**

This part of the survey asks you how you would choose to meet your plant's demands for heat and electricity when faced with different costs and alternative types of technologies.

**For each question, put yourself in the hypothetical situation of needing to replace one of the primary boilers at your facility.** You will be asked to make a simplified choice between a standard efficiency boiler, a high efficiency boiler, and a cogeneration system. Examine the characteristics of the three options presented to you and select the one that you feel best represents the type of technology that your plant would choose in this situation. Assume that each option meets your plant's demand for steam. Keep in mind that your actual choice of heating technology is constrained by your plant's particular characteristics → amount of space available on the plant floor, availability of capital for investments, fluctuation of heat and electricity loads, etc. Answer the questions with this point in mind.

For each choice a simplified economic analysis has been provided consisting of a Net Present Value curve and a payback period, which you can refer to if you are comfortable with, to help you make your decision more realistically. The **Net Present Value (NPV)** curve given shows the discounted present cost of the investment, assuming a 30-year lifespan, at different discount rates. The figure below briefly summarizes the format of the NPV curves in this survey. The **payback period** shows the number of years required for the investments with higher capital costs to pay for themselves through lower operating and/or fuel costs relative to the standard efficiency boiler, which has a lower capital cost. If you are unfamiliar with either or both of these tools, please ignore them and answer the questions based on the characteristics of each alternative technology.

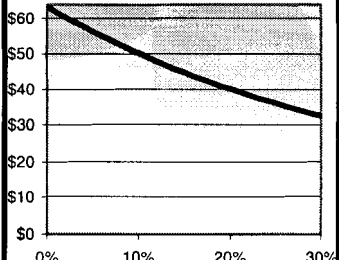
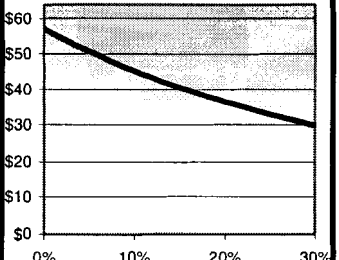
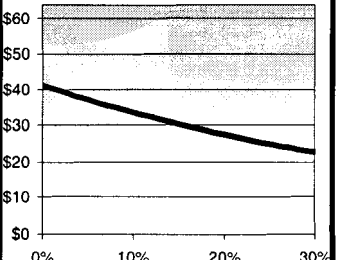
NPV in  
Millions of \$



Discount Rate

The NPV curve allows you to determine the discounted present cost of the investment at different discount (or interest) rates. For example, at a discount rate of 13%, the present cost of the investment is \$8.2M.

8. If you needed to replace one of the primary boilers at your plant and these were the only three options available, you/your firm would choose (tick one):

Option 1: Natural Gas Standard Efficiency Boiler	Option 2: Natural Gas High Efficiency Boiler	Option 3: Natural Gas Cogeneration System
<p><b>Capital Cost</b> \$2,669,000</p> <p><b>Operating Cost</b> \$114,000 / yr</p> <p><b>Thermal Efficiency</b> 76%</p> <p><b>Electrical Efficiency</b> 0%</p> <p><b>Total Fuel Costs</b> \$1,910,000 / yr</p> <p><b>Total Electricity Savings</b> \$0 / yr</p>	<p><b>Capital Cost</b> \$3,662,000</p> <p><b>Operating Cost</b> \$125,000 / yr</p> <p><b>Thermal Efficiency</b> 84%</p> <p><b>Electrical Efficiency</b> 0%</p> <p><b>Total Fuel Costs</b> \$1,651,000 / yr</p> <p><b>Total Electricity Savings</b> \$0 / yr</p>	<p><b>Capital Cost</b> \$4,988,000</p> <p><b>Operating Cost</b> \$170,000 / yr</p> <p><b>Thermal Efficiency</b> 77%</p> <p><b>Electrical Efficiency</b> 8%</p> <p><b>Total Fuel Costs</b> \$1,555,000 / yr</p> <p><b>Total Electricity Savings</b> \$512,000 / yr</p>
		
<p><b>Base Case</b></p>	<p><b>Payback Period</b> 4.0 yr</p>	<p><b>Payback Period</b> 2.9 yr</p>
<p><input type="checkbox"/></p>	<p><input type="checkbox"/></p>	<p><input type="checkbox"/></p>

**Part D – Perspectives on Cogeneration**

12. If your plant does not currently use a cogeneration system, how important are each of the following factors in preventing your plant from using a cogeneration system?

	Importance of factor in deciding not to cogenerate				
	Very Important	Important	Somewhat Important	Not Very Important	Not Important
Inappropriate balance of thermal and electrical loads in your plant	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Cogeneration technologies are unreliable	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
No servicing is available for cogeneration technologies	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Information is not available about cogeneration technologies	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Cogeneration capital costs are too high	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Natural gas prices are too high	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Electricity prices are too low to justify investment	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
The local electric utility policies make selling electricity back to the grid difficult	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Electricity production is not the company's business	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
The local electric utility will not pay reasonable price for electricity generated at the plant	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

13. Do you have any other comments on factors that have prevented your plant from using a cogeneration system?

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14. How do you feel cogeneration systems compare to conventional boiler systems (i.e., a boiler producing only heat; not electricity) in each of the following categories?

	Comparison of cogeneration with boiler					
	Much worse	Worse	Same	Better	Much better	Don't know
Safety	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Reliability	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Capital Cost	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Total Cost (incl. fuel)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Ease of Maintenance	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Environmental Impact	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

15. If the fuel you currently burn most in your boiler(s) became prohibitively expensive, what fuel type would your plant switch to?
- Natural Gas
  - Heavy Fuel Oil
  - Coal
  - Propane or Butane Liquids
  - Middle Distillates
  - Other \_\_\_\_\_
16. Approximately how much more expensive would the fuel your plant currently uses have to become before you switched to the fuel type you answered in question 9?
- Less than 10%
  - Between 10 and 30%
  - Greater than 30%
17. If your plant required new heating capacity in the coming year, would a cogeneration system be considered?
- Yes
  - No

**Part E – Energy Policies**

18. There are many policies that the Government could use to affect the energy efficiency of industry. Rate each of the following policies according to how acceptable they would be to you/your plant.

	Acceptability of policy						
	Completely Unacceptable	Somewhat Unacceptable	Neutral	Somewhat Acceptable	Completely Acceptable	Don't Know	
<b>Information Programs</b> – government provides information about energy efficient technologies	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
<b>Investment Subsidies</b> – government subsidizes energy efficient technologies	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
<b>Energy Taxes</b> – government taxes energy, revenue goes to government for spending	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
<b>Recycled Energy Taxes</b> – government taxes energy; revenue is used to lower labour or other taxes	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
<b>Technology Standards</b> – government mandates what technologies are permitted and what ones are not	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	

19. How important is it that Canada's energy efficiency policies are comparable to those of the United States?

- Not at all important → Canada should develop policies based on our own needs
- Somewhat important → Canada should balance our needs with current US policies
- Very important → Canada needs to follow the US in order to remain competitive

20. Do you have any further comments on government policies on energy efficiency in industry or anything else in this survey?

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Notes:

- This survey was printed in booklet form on legal sized paper
- This survey was available in French as well as English
- Questions 9-11 have been left out of the survey in this appendix to conserve space. They are similar to question 8.

## Appendix 5 – CIMS steam generation technology database

Table 4A – 12 MW Thermal Output

		Capital Cost	Operating and Maintenance Cost	Thermal Efficiency	Electrical Efficiency
<b>Hog Fuel</b>					
600 psig	SEB	\$9,423,000	\$377,000	65.50%	0.00%
	HEB	\$14,134,500	\$565,500	71.00%	0.00%
	COG	\$12,063,000	\$495,000	65.60%	6.80%
900 psig	SEB	\$11,590,000	\$463,000	65.60%	0.00%
	HEB	\$17,385,000	\$694,500	71.00%	0.00%
	COG	\$14,230,000	\$581,000	58.70%	6.50%
1250 psig	SEB	\$14,135,000	\$565,000	65.60%	0.00%
	HEB	\$21,202,500	\$847,500	71.00%	0.00%
	COG	\$16,775,000	\$683,000	65.60%	9.10%
<b>Natural Gas</b>					
600 psig	SEB	\$2,355,000	\$94,000	75.90%	0.00%
	HEB	\$3,532,500	\$141,000	80.20%	0.00%
	COG	\$4,995,000	\$212,000	78.00%	8.00%
900 psig	SEB	\$2,897,000	\$115,000	75.90%	0.00%
	HEB	\$4,345,500	\$172,500	80.20%	0.00%
	COG	\$5,537,000	\$233,000	68.00%	7.50%
1250 psig	SEB	\$3,500,000	\$141,000	75.90%	0.00%
	HEB	\$5,250,000	\$211,500	80.20%	0.00%
	COG	\$6,140,000	\$259,000	75.90%	10.50%
<b>Heavy Fuel Oil</b>					
600 psig	SEB	\$2,400,000	\$98,000	79.70%	0.00%
	HEB	\$3,600,000	\$147,000	83.40%	0.00%
	COG	\$5,040,000	\$216,000	79.70%	8.20%
900 psig	SEB	\$3,000,000	\$121,000	79.70%	0.00%
	HEB	\$4,500,000	\$181,500	83.40%	0.00%
	COG	\$5,640,000	\$239,000	71.30%	7.90%
1250 psig	SEB	\$3,700,000	\$148,000	79.70%	0.00%
	HEB	\$5,550,000	\$222,000	83.40%	0.00%
	COG	\$6,340,000	\$266,000	79.70%	11.00%
<b>Coal</b>					
600 psig	SEB	\$7,000,000	\$282,000	81.60%	0.00%
	HEB	\$10,500,000	\$423,000	85.00%	0.00%
	COG	\$9,640,000	\$400,000	81.60%	8.40%
900 psig	SEB	\$8,700,000	\$347,000	81.60%	0.00%
	HEB	\$13,050,000	\$520,500	85.00%	0.00%
	COG	\$11,340,000	\$465,000	73.00%	8.10%
1250 psig	SEB	\$10,600,000	\$424,000	81.60%	0.00%
	HEB	\$15,900,000	\$636,000	85.00%	0.00%
	COG	\$13,240,000	\$542,000	81.60%	11.20%

**Table 4B – 100 MW Thermal Output**

		Operating and	Thermal	Electrical	
		Capital Cost	Maintenance Cost	Efficiency	
		Fuel			
		Capital Cost	Maintenance Cost	Efficiency	
600 psig	SEB	\$34,200,000	\$1,368,000	65.60%	0.00%
	HEB	\$51,300,000	\$2,052,000	71.00%	0.00%
	COG	\$45,000,000	\$1,801,000	65.60%	6.80%
900 psig	SEB	\$42,000,000	\$1,682,000	65.60%	0.00%
	HEB	\$63,000,000	\$2,523,000	71.00%	0.00%
	COG	\$52,800,000	\$2,115,000	58.70%	6.50%
1250 psig	SEB	\$51,300,000	\$2,000,000	65.60%	0.00%
	HEB	\$76,950,000	\$3,000,000	71.00%	0.00%
	COG	\$62,100,000	\$2,433,000	65.60%	9.10%
<b>Natural Gas</b>					
600 psig	SEB	\$8,550,000	\$342,000	75.90%	0.00%
	HEB	\$12,825,000	\$513,000	80.20%	0.00%
	COG	\$19,350,000	\$775,000	78.00%	8.00%
900 psig	SEB	\$10,500,000	\$420,000	75.90%	0.00%
	HEB	\$15,750,000	\$630,000	80.20%	0.00%
	COG	\$21,300,000	\$853,000	68.00%	7.50%
1250 psig	SEB	\$12,800,000	\$513,000	75.90%	0.00%
	HEB	\$19,200,000	\$769,500	80.20%	0.00%
	COG	\$23,600,000	\$946,000	75.90%	10.50%
<b>Heavy Fuel Oil</b>					
600 psig	SEB	\$9,000,000	\$360,000	79.70%	0.00%
	HEB	\$13,500,000	\$540,000	83.40%	0.00%
	COG	\$19,800,000	\$793,000	79.70%	8.20%
900 psig	SEB	\$11,000,000	\$441,000	79.70%	0.00%
	HEB	\$16,500,000	\$661,500	83.40%	0.00%
	COG	\$21,800,000	\$874,000	71.30%	7.90%
1250 psig	SEB	\$14,500,000	\$539,000	79.70%	0.00%
	HEB	\$21,750,000	\$808,500	83.40%	0.00%
	COG	\$25,300,000	\$972,000	79.70%	11.00%
<b>Coal</b>					
600 psig	SEB	\$25,700,000	\$1,026,000	81.60%	0.00%
	HEB	\$38,550,000	\$1,539,000	85.00%	0.00%
	COG	\$36,500,000	\$1,459,000	81.60%	8.40%
900 psig	SEB	\$31,500,000	\$1,261,000	81.60%	0.00%
	HEB	\$47,250,000	\$1,891,500	85.00%	0.00%
	COG	\$42,300,000	\$1,694,000	73.00%	8.10%
1250 psig	SEB	\$38,475,000	\$1,500,000	81.60%	0.00%
	HEB	\$57,712,500	\$2,250,000	85.00%	0.00%
	COG	\$49,275,000	\$1,933,000	81.60%	11.20%



## **Appendix 6 – Mail survey correspondence**

### **5A – INITIAL COVER LETTER**

<<Plant Manager, Company>>:

October 10, 2002

This package is a follow-up to our recent telephone conversation with you in which you provided us with some information on energy use in your plant. Included in this package is a brief questionnaire in which we seek to determine your preferences towards different heat and electricity generation technologies. We appreciate your help and advice with this important research.

The results of this survey will help to guide energy policy formulation by the Office of Energy Efficiency as well as to enhance technology simulation models developed at Simon Fraser University. This research is supported by funding from the Office of Energy Efficiency.

It will greatly assist our research if you answer all the questions as completely and accurately as possible. Please take the opportunity to provide your input on these important issues by taking about 15 minutes to fill out the survey and return it to us in the enclosed postage paid envelope. We appreciate that this request for your limited time is probably inconvenient.

Be assured that your answers will be held confidential. All information collected through this survey will be released only in summary, and no individual answers will be identified. Neither you nor your plant will be tied with any information you provide. Once you have returned a completed survey, we will delete your firm's name from our records so that answers are not associated with a particular person or firm. Your participation in this survey is voluntary, and we will assume that by completing and returning this survey you are indicating your consent to participate in this research.

If you have any questions or concerns about this research, we would be glad to talk to you. If you have specific questions or concerns about the survey please leave a message for the primary researcher, Nic Rivers, on the survey line at (604) 268-6621 or via email at [njrivers@sfu.ca](mailto:njrivers@sfu.ca). All messages are returned the following day. More general concerns about the research can be directed to Frank Gobas, Director of the School of Resource and Environmental Management at Simon Fraser University, at (604) 291-5928.

Thank you very much for your time. Your help with this survey is greatly appreciated.

Sincerely,

Nic Rivers  
Energy and Materials Research Group  
School of Resource and Environmental Management

Simon Fraser University

## **5B – POSTCARD**

Dear <<Plant Manager, Company>>:

A week ago, you were sent your copy of the Industrial Heating Technology Survey. If you have already completed and returned the survey, we want to express our appreciation for your help with this research project.

If you didn't receive your copy of the survey, or if you have misplaced it, please contact us and we will send you a replacement immediately. You can leave a message by telephone on the survey line at (604) 268-6621, or by email at njrivers@sfu.ca. Please provide your name, telephone number, and address in the case that your first copy was sent to a wrong address.

If you received your survey but have not yet completed it, we encourage you to take about 15 minutes to fill it out and mail it to us at the address indicated on its back cover. Your input will help to provide the basis for future energy policies.

Thank you again for your participation in this project.

Nic Rivers  
Energy and Materials Research Group  
Simon Fraser University

## **5C – FINAL FOLLOW UP LETTER**

<<First Name, Last Name>>  
COMPANY NAME

November 26, 2002

<<First Name, Last Name>>:

Several weeks ago, you were sent a copy of the Industrial Heating Technology Survey. To the best of my knowledge, it has not been returned as of November 26, 2002.

Respondents who have already returned their surveys have provided a wealth of information on factors influencing the adoption of specific technologies by industry. The pooled results of the survey will help to guide government policy makers and analysts designing and evaluating energy policies for the future.

However, in order for the results of the survey to be truly representative of the opinions of industry as a whole, it is important that we hear back from as many people as possible. Your opinions are important, and we want to know what you think about the questions

and choices presented in the survey. By returning your survey, you will help make the results of the research more accurate.

If you have any questions about the survey or research please leave a message by phone on the survey contact line at (604) 268-6621 or by email at [njrivers@sfu.ca](mailto:njrivers@sfu.ca). Both the voice mail and email are checked daily and any messages are returned the next day.

We hope you will fill out the enclosed survey and return it, but if for any reason you prefer not to complete it, please let us know by returning the blank survey or a brief note in the enclosed stamped envelope.

This is the last time that you will be contacted regarding this survey. **Please mail the survey by December 6, 2002 to be included in the results.**

Thank you for your time and assistance.

Sincerely,

Nic Rivers  
Energy and Materials Research Group  
Simon Fraser University