

**MODELLING CONSUMER PREFERENCES
AND TECHNOLOGICAL CHANGE:
SURVEY OF ATTITUDES TO HYBRID VEHICLES**

by

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ABSTRACT

The goal of this research project was to introduce realistic consumer decision behaviour of choosing between newer low-emission vehicle technologies and the conventional vehicle technology into the CIMS model. This is a “hybrid” energy economy model that combines behavioural realism, macroeconomic feedback, and technology explicitness into its simulations to facilitate useful modelling outputs for policy makers to make better policy decisions. My research focused on quantifying the consumer’s decision process between the hybrid gas-electric vehicle (HEV) and the conventional gasoline vehicle with increased market penetration (“the neighbour effect”). Through the use of a national survey and the building of a discrete choice model, I found that consumer values for non-monetary attributes change with market shares of HEVs. This novel finding was translated into CIMS model parameters in order to perform policy simulations that are more behaviourally realistic.

DEDICATION

I would like to dedicate this to my Mom and Dad, and my wife Poh for all of your emotional support and encouragement.

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1 INTRODUCTION

In recent years, policy makers have been confronted with demands to address a variety of environmental goals. These include reducing carbon emissions to reduce global warming, minimizing release of substances that thin the ozone layers, and reducing airborne pollutants that cause respiratory and other health problems.

To design effective policies to achieve such environmental goals, government policy makers require different types of information. Information can come from various sources. For familiar situations, policy makers can rely on past experiences, expert and public opinion, and results from past scientific studies. However, in new situations or in cases where the decision-makers expect to meet the policy goal in the long term, information is often limited or incomplete. In these cases, policy makers often consult simulation models to make the best use of the limited information. In particular, due to a lack of experience and prior direct information, models play a large role in decision making with respect to climate change policies. For instance, in the year 2000, the Canadian National Climate Change Process selected four energy-economy models to simulate the cost of lowering greenhouse gas emissions through technological change under different management actions (AMG, 2000). One of the four models was a “bottom-up” model, which simulates technological change based on financial cost comparisons. Two of the four models were “top-down” models, which simulate technological change based on historical data on aggregate relationships in the market. The fourth model, CIMS, was a hybrid model developed by the Energy and Materials Research Group (EMRG) at Simon Fraser University (SFU). CIMS incorporated the features of bottom-up and top-down models.

To set effective policies, it is essential that these aforementioned energy-economy models provide the most realistic projections possible based on the best available data. To be useful, the models should include detailed costs for alternative technologies; these costs include expenses associated with obtaining, operating, and maintaining the technologies. More importantly, useful models should also include a realistic portrayal of consumer behaviour, namely, how consumers choose among different technologies that offer similar services.

While each of the four models can effectively model policy problems that are specific to their own disciplines, they are inadequate in modelling the social costs of broad scale environmental policies that often require the understanding of consumer behaviour toward specific technologies. The bottom-up models have high financial detail with respect to technologies, but tend to have insufficient information related to consumer behaviour, leading to policy cost estimates that are too low. In contrast, the top-down models are explicit in modelling consumer behaviour, but generally lack detailed technological representation, leading to policy cost estimates that are too high. The CIMS hybrid model incorporates high technological financial detail and macroeconomic feedbacks, but it needs to improve its portrayal in consumer behaviour for each individual technology. Although CIMS' current cost estimates are between those of bottom-up and top-down models, these costs have high uncertainty. In particular, CIMS' portrayal of consumer decisions needs to improve in order to be able to simulate the effects of policies aimed at causing profound technological change in the long run.

This research project is part of a concerted effort in filling the consumer behaviour knowledge gap at CIMS. Past research by the CIMS modelling group has focused on building the behavioural components in CIMS for technologies associated

with the industrial sector and transportation modes under non-changing (static) market conditions. This research focuses on the behavioural component in CIMS for evolutionary technologies under changing (dynamic) market conditions. Evolutionary technologies are new technologies that provide the same service as a current technology without requiring significant changes in current infrastructure. The Hybrid Gas-Electric vehicle (HEV), an example of an evolutionary technology, is the focus of my study. This passenger vehicle technology has gained a high profile in industry and government, and is the next logical step in reducing greenhouse gas emissions from passenger vehicles. No new infrastructure requirements, such as new fuelling stations, are needed before it can be widely adopted. Most importantly, the financial costs of Hybrid Gas-Electric passenger vehicles are well known, and the demand and supply of passenger vehicles has been well established by past market data. Thus, the behavioural component of this technology can be investigated without interference from high uncertainty in the aforementioned infrastructure requirements, financial costs, and demand and supply of passenger vehicles.

My research provides value to the field of energy-economy modelling by advancing CIMS to better incorporate consumer behaviour in a dynamic market. In order to facilitate this understanding, I have developed an empirical model based on a consumer survey.

The remainder of this chapter provides: (1) background information on energy-economy models, including brief descriptions of how they represent technological change; (2) a description of CIMS; (3) an introduction to choice modelling, the foundation used in this research to model consumer behaviour; and (4) a brief background on new technologies and hybrid electric vehicles. This chapter closes with a summary to justify the importance and relevance of this research.

1.1 Traditional models for technological change

Two broad categories of energy-economy models are used to estimate the costs associated with technological change: bottom-up models and top-down models. These models differ in how they address three main points: technology explicitness, representation of consumer behaviour, and the incorporation of macroeconomic feedbacks (Jaccard et al., 2003):

	Technology Explicitness	Representation of consumer behaviour	Macroeconomic feedbacks
Bottom-Up	High	Low	Low
Top-Down	Low	High	High

Table 1 - traditional models for technological change

“Technology explicitness” of a model refers to the level of detail in cataloguing the stocks of technologies and their respective characteristics. These details can include capital costs, operating costs, and maintenance costs of individual technologies. These details can also extend to non-monetary characteristics, such as performance, efficiency, emissions profile, and service outputs.

“Representation of consumer behaviour” in a model is how well the model captures the consumer’s decision-making process in competing technologies. Models that accurately capture consumer behaviour from empirical data are considered to be behaviourally realistic. In addition to many financial variables about the technologies in question, which are each technology’s capital cost and operating cost, behaviourally realistic models can also include demographics, such as consumer income, perceptions of risk, and the desire for new technologies. In contrast, behaviourally weak policy models do not incorporate all of these factors in determining technological adoption by

consumers; some resort to simple decision rules such as adopting technologies solely on the basis of financial costs.

Models with macroeconomic feedback attempt to determine the equilibrium effects of a given policy. That is, they describe how policies affect the normal, prevailing conditions of a market. In these models, policies are seen as temporary disturbances to the supply, demand, and prices of the energy sector. Given time, the initial response to these policies may change as the energy sector adjusts to this shock and returns to equilibrium. Energy policies that cause large impacts within the energy sector might also cause a disturbance outside of the sector, leading to precipitating adjustments in the whole economy, including changes in employment and trade. Models that simulate additional feedback beyond the energy sector are “general equilibrium models”. Models that only incorporate the equilibrium effects of the energy sector are “partial equilibrium models”. Ideally, all policy decisions should consult general equilibrium models to assess the extent of the decision’s final impact. However, this process can potentially be very complex, and often a partial equilibrium model is adequate in providing a satisfactory illustration of policy projections.

Bottom-up energy-economy models are technologically explicit but not behaviourally realistic. The base of a bottom-up model is a database of detailed technology data, which involves the lifetime financial costs associated with a stock of technologies. In modelling policies, bottom-up models generally depict consumers as price optimizers using, for example, a linear programming algorithm. That is, consumers in aggregate will pursue the cheapest technology amongst a group of technologies that perform the same service. The use of this rule bears several important assumptions. The first assumption is perfect information: consumers are assumed to have all the financial information about all of the technology choices available to them. The second

assumption is perfect foresight: consumers are assumed to foresee all potential technologies that will provide the services they will seek in the future, optimizing their technology choice as a path of least cost over time. The third assumption is a fully competitive market: consumers have access to all technologies without barriers. In an open economy, few consumers have perfect information and perfect foresight. Few markets are fully competitive, due to barriers such as geographical distance and imperfect information. Experience and recent studies have also shown that consumers are not usually price optimizers, because their choices are partly influenced by non-financial aspects of a technology (Horne, 2003; Rivers, 2003; Ewing & Sarigollu, 2000). The oversimplification of the economy by bottom-up models through these assumptions can result in inadequate portrayals of consumer decisions. Thus, bottom-up models tend to underestimate the social costs of policies. For example, one of the four bottom-up models chosen by the government of Canada to model greenhouse gas policies, MARKAL, has consistently projected relatively low policy costs (Loulou et al., 2000; Loulou et al., 1999).

In contrast, top-down models rely heavily on historical market data to estimate relationships between aggregate outputs and inputs (energy, capital, labour, materials) to project future outcomes. Since top-down models are based on historical interactions, they are behaviourally realistic. However, there are three major assumptions in top-down models that limit their ability to forecast realistic costs. First, they assume that past market behaviour corresponds to market behaviour in the future. Second, they assume that any shocks to the status quo will result in costs. Third, they do not identify individual technologies. As a result of these three assumptions, top-down models are less useful in projecting policies that target specific sets of technologies. Also, for policies that have a general target for all technologies, top-down models have a

tendency to overestimate their costs. For instance, the two top-down models TIM and CaSGEM used by the Canadian National Climate Change Process had high cost projections of greenhouse gas policies in comparison to the bottom-up model MARKAL (AMG, 2000).

1.2 Modelling technological change using CIMS, a hybrid model

CIMS, a hybrid energy-economy model combining the strengths of both bottom-up and top-down models, was created by the Energy and Materials Research Group (EMRG) at Simon Fraser University (SFU) (Jaccard et al., 2003). This model has a high degree of technological detail and is capable of modelling the adoption and retirement of individual technologies. This model also has the capacity to realistically portray consumer behaviour beyond the sole consideration of financial costs and has the ability to capture the relationship between the energy sector and the rest of the economy in a broader macroeconomic framework.

CIMS' level of technological detail is similar to many bottom-up models such that it keeps a detailed account of technology characteristics over time, including capital stock turn over, service outputs, financial costs, and emissions. All of the technological details in CIMS are disaggregated; the evolution of each technology can be traced to the final outputs. During a simulation, the older technologies are discarded (retired) according to their unique age-dependent functions, and they can be constrained to meet pre-determined minimum and maximum market shares.

The representation of consumer behaviour in energy-economy models determines how the technology stock evolves. CIMS evolves technology stocks by comparing the life cycle costs between technologies that provide a similar service. Specifically, CIMS determines the total costs a technology will incur over its lifetime

adjusted by a discount rate. Similar to bottom-up models, CIMS assumes consumers will choose a technology that has the lowest life cycle cost. However, to improve the representation of consumer behaviour, CIMS defines life cycle costs differently than bottom-up models. First, CIMS includes monetized costs from qualitative characteristics. Second, in contrast to traditional bottom-up models that assume all consumers make identical decisions, CIMS recognizes that, for a variety of reasons, all consumers might not value technologies equally.

Macroeconomic feedback in CIMS comes from the integration of energy supply and demand and the macroeconomic performance of key sectors of the economy, including trade effects. Consumers and businesses make technology decisions based on limited foresight. During a policy simulation in CIMS, the new stocks for particular technologies equilibrate between the different sectors at each time period due to shocks to demand and supply induced by the policies.

Although CIMS has inherited the advantages of traditional top-down and bottom-up models, it has also inherited two challenges in estimating the cost of technological change. The first challenge is the uncertainty related to the financial cost of a technology as its production increases. Generally, financial costs for a given technology decline with production due to economies of scale and learning, generating “experience curves” (Azar and Dowlatabadi, 1999; Duke and Kammen, 1999). CIMS incorporates these experience curves by way of a declining capital cost function for each technology.

The second challenge is uncertainty in the rate of adoption for new technologies. Consumers’ propensity to adopt a new product or a new technology is partially affected by the consumer surplus: the extra value that consumers realize above the financial cost of a particular technology (Jaccard et al., 2004). Although modellers must characterize consumer surplus as a monetary value, it represents consumer preferences for non-

financial characteristics, such as aesthetic beauty, uniqueness, and perceived usefulness. Austin and Macauley (1998) have shown that the people's perceptions of extra value in new technologies over the conventional ones are low because individual consumers are reluctant to change. This is partly because the conventional technologies have a high "option value", the expected gain from delaying or avoiding an investment (Pindyck, 1991). For instance, in the automotive industry, unconventional vehicle-drive trains, such as hybrid gasoline-electric, increase the perceived risks for some consumers, and energy efficient vehicles can have higher up front costs, which increase the risk of not realizing the payback on this extra investment (Jaccard et al., 2004).

When consumers are induced or forced to switch away from the conventional technology to a new technology, economists say that the social cost of this switch is the difference in financial costs plus any intangible costs, such as option value and consumer's surplus (Jaccard et al., 2004). However, this social cost is dynamic depending on the market conditions, and if the financial cost of the conventional and new technologies are similar, then the social cost of the technology switch can be referred to as a net loss of consumer surplus of the new technology. However, this loss may decline as new technologies gain acceptance, which may then result in a higher acceptance in the next time period, leading to an adoption rate of new technologies that is exponential in shape (Austin & Macauley, 1998). In marketing research, this trend is called an adoption curve (Mahajan, 1990). Research has shown that the initial adoption rate of a technology is a function of the acceptance rate of consumer groups, who have a high initial desire for new technologies are the "innovators" and the "early adopters". By first adopting the new technologies, they lower the loss in consumer surplus for others, which leads to higher adoption of the new technologies (Frank, 2002; Mahajan,

Muller, & Bass, 1990). CIMS is able to represent such consumer surplus effects on the adoption of each technology by an “intangible cost function”. For conventional technologies, the intangible cost function can be derived from historical market data. For new technologies, this function can be estimated from discrete choice models built from consumer preference surveys.

1.3 Discrete Choice models

Traditionally, economists quantify consumer preferences and demands in aggregate and analyze these aggregate numbers by modelling them as continuous variables. That is, the model’s variables can assume any value within a predefined range (Train, 1986). The models that describe these continuous variables are called continuous choice models. These models can characterize consumer demands through statistical regression between the continuous variables. For example, a macroeconomic model may represent future consumer vehicle purchases as a function of energy cost, with the modelling parameters informed by historical economic data. The modelling outputs of this example might be reported as continuous values, such as a gasoline price of 89 cents/L will lead to vehicle purchase of 1.11 vehicles/person.

Many economic literatures describe the use of continuous choice models to model consumer behaviour, such as preferences for insurance and attitudes toward self selection. However, such continuous models present limitations to policy makers who wish to develop policies aimed at encouraging the adoption of new technologies by targeting the technologies’ specific aspects. This level of precision requires an understanding of the actual process of how consumers decide between technologies at the individual level and how they value each aspect of the technology. For example, a consumer cannot choose to purchase 1.11 fuel efficient vehicles when gasoline prices are 89cents. Nor can a consumer purchase a vehicle that runs on 10% gasoline and

90% diesel. Rather, these individual decisions are discrete. When faced with a certain situation, consumers either choose to buy a fuel efficient vehicle or not, and if they do buy one, they either obtain one that is fuelled by gasoline or by diesel. Models that describe such discrete individual decisions are called discrete choice models (Train, 1986).

Aside from the difference in the conceptual details between continuous and discrete choice models, their structures are also fundamentally different. For example, discrete choice models have a rigid definition of consumer choice. Consumer decisions are assumed to be valued-based, and their behaviour is expressed as a probabilistic value. The input requirements in discrete choice models are also much more precise and focused on consumers as individuals. In contrast, continuous discrete choice models express their outputs as deterministic (one number), and most assume all consumers to behave in the same way.

Consumer decisions in discrete choice models are defined as a single choice from a set of alternatives. To effectively model these decisions, alternatives must meet five criteria. First, the number of alternatives should be finite. Second, the set of alternatives should be exhaustive. That is, they need to represent all possible choices available to the consumer. Third, the alternatives should be mutually exclusive. Fourth, each of the alternatives can be described by a list of characteristics, such as size, colour, and price. Fifth, each alternative can be distinguished from another based on this list (Bennett & Blamey, 2001; Train, 1986).

The discrete choice model assumes consumers value certain characteristics of each alternative, and their final choice is the one that provides them with the highest value. In economic terms, the consumer's decision is assumed to have the highest "utility" relative to the pool of all available choices. To model this consumer decision

process, the relative value each consumer places on each characteristic for the alternatives is reduced to a number. The numbers associated with each characteristic are then aggregated to estimate a utility function, from which the utility of each alternative can be calculated. The utility of each alternative is then used to form a ratio, which expresses how consumers value each alternative over all others. This ratio can be expressed as the probability of a consumer choosing one technology over another. Generally, the higher the utility of one technology as compared to the alternatives, the higher is the probability that the consumers will adopt the technology. This probability is the output of most discrete choice models and is more informative to policy makers in understanding consumer behaviour than outputs from continuous choice models. It provides a quantifiable degree of acceptance to different alternatives, rather than reporting if a technology will be adopted or not.

To build a discrete choice model, the analyst requires a list of available alternatives, the most commonly valued characteristics of these alternatives, and a record of consumer choices regarding these alternatives. Discrete choice models that describe historic or current technologies can obtain this information from historical market data such as sales records. For new technologies, where no such records exist, the most valued characteristics may be estimated from similar existing technologies; however, the record of consumer choice must be solicited through a consumer survey. The “stated preference survey” is one type of consumer survey that presents different alternatives to survey participants by describing actual or hypothetical characteristics of the technologies under study. Survey participants are asked to choose a preferred technology based on these descriptions, and this collection of hypothetical consumer choices makes up a record of consumer decisions for the discrete choice model.

Building discrete choice models from stated preference surveys has been a popular method among researchers. They have used this method extensively in a variety of fields, from modelling future transportation choices (Train, 1986) to proposed tenant regulation and policies (Walker et al., 2001). The advantage with stated preference surveys is that the investigator can test many hypothetical alternatives at once, thus enabling policy makers to efficiently estimate the consumer response to different but related policies. However, in comparison to models relying on historic market data, discrete choice models relying on stated preference surveys may have results that are less reliable due to the complete reliance on the respondent's survey responses. The respondents' stated decisions may differ from their actual decisions when they are faced with real world conditions, and hence the model results might not properly reflect reality (Bennett & Blamey, 2001).

1.4 Evolutive technologies

New technologies can be classified into two general categories: "disruptive" and "evolutionary" (Christensen, 1997). This categorization is mainly based on two factors. The first factor is the uniqueness of the new technology relative to the conventional technology that provides the same service. The second factor is the transaction cost, namely, the costs pertaining to the time and money consumers and businesses need to spend in learning and supporting these technologies. Due to these different factors, consumers might respond differently to disruptive and evolutionary technologies. Thus, these differing consumer responses would be important to capture in the behavioural component of energy-economy models.

Disruptive technologies have unique attributes that are not present in conventional technologies. Disruptive technologies may also use very different strategies to provide a similar service as the conventional technologies. Often, the

introduction of disruptive technologies incurs high transaction costs in the form of infrastructural changes (Jackson, 2003; Christenson, 1997). For example, the hydrogen fuel cell vehicle is a disruptive technology in the transportation sector. A new supporting infrastructure, including new hydrogen manufacturing facilities, new delivery systems, new safety systems, and new maintenance procedures, will have to be developed by the time the first hydrogen fuel cell vehicle is available for sale in neighbourhood dealerships. Once the consumers acquire the new hydrogen fuel cell vehicle, they will need to invest a large amount of time in learning about the vehicle before the vehicle can be operated and maintained. Such high transaction costs are significant barriers to the adoption of disruptive technologies in the market.

In contrast, evolutionary technologies are new technologies that represent small improvements to the conventional technologies. Although some learning has to take place to successfully launch evolutionary technologies, their introduction requires low transaction costs due to their ability to take advantage of the current infrastructure for the conventional technologies. The hybrid gas-electric vehicle (HEV) is an example of an evolutionary technology competing with the conventional gasoline vehicle. The HEV runs on gasoline; its internal drive mechanics are similar to those of the conventional gasoline engine; and consumers do not need to invest a large amount of time learning about the HEV before they can operate and maintain it. However, the similarity of evolutionary technologies to conventional technologies may prevent consumers from clearly understanding the additional benefits that these new technologies may provide over the existing technologies. Hence, the lack of uniqueness may serve as a barrier to their adoption, with consumers seeing little benefit in making any changes to their vehicle purchase decisions.

Current energy-economy models that consider consumer behaviour do not explicitly treat consumer responses associated with different technology categories differently. Since the barriers to adoption for technologies in different technology categories are very different, policies that are modelled based on evolutionary technologies may not be suitable for disruptive technologies, and vice versa. Thus, it is important that consumer behaviour to these technology categories are embedded in energy-economy models such as CIMS in order to provide better information for policy makers.

1.5 Hybrid gas electric vehicles

The hybrid gas-electric vehicle (HEV) , or, more commonly referred to as the “hybrid vehicle” is a new vehicle technology that was introduced to the North American consumer market in 2001 (Autonews, 2003). These vehicles are built to reduce tailpipe emissions and to improve mileage to combat municipal air pollution, global warming, and uncertain future fuel prices. For instance, the passenger versions of HEVs, such as the Honda Insight and Honda Civic Hybrid, can drive 1.5 to 2.0 times further per litre of gasoline than conventional vehicles of a comparative class (Honda, 2004).

The main difference that consumers notice between the HEV and the conventional gasoline vehicle is the HEV's high fuel efficiency, mainly achieved by using a small gasoline engine coupled to an electric motor to power the vehicle. Unlike conventional gasoline engines, which are designed to meet the power demands of every driving condition, the HEV engine is designed to only meet the average power requirements, such as cruising on flat terrain. Thus, it has lower horsepower ratings, a smaller size, and a low weight - all factors that lead to higher fuel efficiency. When driving conditions in a HEV become more demanding, such as on uphill terrains, its electric motor provides the extra power to move the vehicle forward, with the energy

coming from on-board batteries. These batteries are typically charged by a process called “regenerative braking”. That is, during downhill cruising or regular braking, the electric motor slows the vehicle down along with the regular brakes, acting as an electric generator to charge the on-board batteries. Thus, the HEV is able to conserve energy in its batteries that would otherwise be wasted in the conventional vehicle.

In addition to the design of the aforementioned power system, hybrid vehicles manufactured by different companies also have features to further improve fuel efficiency. For example, the Toyota designed its “Prius” to eliminate engine idling by shutting off the gasoline engine and only powering the vehicle with its electric motor during periodic stops in the city; Honda designed its “Insight” to be aerodynamic to reduce drag.

Aside from the technical innovations focused on high fuel efficiency, the HEV technology is very similar to conventional gasoline vehicles. They both consume the same fuel. They also both have the same maintenance schedules and operating procedures. Consumers and mechanics who are familiar with conventional vehicles will require little training to become accustomed to HEV's (Honda, 2004). The introduction of HEV technology has few barriers from a transaction cost standpoint, and its adoption can greatly reduce the consumption of gasoline and reduce greenhouse gas emissions in the transportation sector. Thus, the HEV is an excellent technology option to be examined and analyzed by policy makers who are involved in setting greenhouse gas policies (Horne, 2003; Ewing and Sarigollu, 2000).

1.6 Summary and research objectives

Traditional top-down and bottom-up energy-economy models do not provide enough information to policy makers seeking to estimate the social costs of environmental policies. Hybrid energy-economy models that have been developed to address this problem, such as CIMS, have excelled in terms of technological detail and macroeconomic feedback. However, their portrayal of consumer behaviour toward specific technologies still needs to significantly improve.

Past studies, which focused on the industrial sector and personal transportation under static market conditions, have contributed to the portrayal of consumer behaviour in CIMS (Rivers 2003, Horne 2003). Similar to other consumer behaviour studies, the focus of investigation was on the relationship of consumer values to a specific set of technologies and how these values, without manipulating market conditions, influence consumers' purchasing behaviour (Brownstone et al., 2000; Ewing & Sarigollu, 2000; Brownstone & Train, 1999; Greene, 1997; Bunch et al., 1993). For example, Rivers (2003) investigated how industrial purchasing decisions are influenced by the values consumers place on subsidies, efficiencies, costs, and payback periods. Horne (2003) investigated how consumers based their decision making between vehicle technologies and transit options on the values associated with financial costs, power, emissions, and road access.

However, consumer decision processes are not limited by technology attributes. Two important external factors may also influence a consumer's decision. First, a consumer's decision on a technology may be influenced by the responses of other consumers towards the same technology. That is, consumer behaviour may change as a function of market conditions, where the technology gain or lose market shares - a relationship that is also referred to as the "neighbour effect". Second, a consumer's

decision process may also differ depending on whether the new technology is disruptive or evolutionary. Understanding both of these aspects in consumer's decision-making process is important for modelling consumer behaviour in energy-economy models such as CIMS, because these aspects are uncertainties that can significantly affect the modelling outcome.

This research paper directly addresses these two aspects of consumer behaviour by modelling the consumer behaviour associated with evolutionary technologies under different market conditions. Specifically, the null hypothesis in this research is that market conditions do not affect how consumers value different aspects of a new technology, leading to no differences in their decisions. A companion paper by Eyzaguirre (2004) investigates consumer behaviour associated with disruptive technologies. The combination of these two studies should provide a greater understanding of modelling implications of consumer behaviour towards new technologies. This study focuses only on the adoption dynamics of HEVs because: (1) this is clearly a new evolutionary technology, and (2) its high fuel efficiency can make a large impact in reducing vehicle emissions from the passenger fleet. Hence, policy makers would likely be interested in pushing for policies that aid in the adoption of HEVs in the passenger vehicle market. Additionally, HEVs are simpler to model than other new evolutionary technologies because the technical specifications are well known and can easily be obtained from vehicle manufacturers. Furthermore, this technology has received much media attention and, thus, has considerable consumer recognition. Therefore, it is expected that survey participants in this research would be more able to provide precise information on the preference surveys.

The remainder of this paper presents a choice modelling study aimed at understanding consumer behaviour regarding hybrid electric vehicles. Specifically,

Chapter 2 describes the methods used in this study. Chapter 3 presents the behavioural model estimated from discrete choice modelling. Chapter 4 describes the conversion of the results from the discrete choice model into the hybrid energy-economy model, CIMS. Chapter 5 presents a demonstration of policy simulations using CIMS with the improved behavioural component as informed from results of this research. Chapter 6 concludes this paper and presents recommendations for future research.

2 METHOD

Four steps are required to meet the objective of this research. The first is to design a choice experiment that collects consumer responses to HEVs under different market conditions. The second is to estimate discrete choice models from these data. The third is to formulate an empirical relationship by analyzing and comparing the qualitative model results under each market condition. The fourth is to translate this relationship into parameters for the intangible cost function in the CIMS energy-economy model.

Since consumer values are inherently different from one consumer to another, discrete choice models cannot represent the exact value judgements and decision processes of all consumers. It is important to characterize these uncertainties because they establish how believable the modelling results are. Therefore, as a fifth step, I characterized the uncertainties in the discrete choice models using the Bayesian approach, which reports the probability of each parameter in the model, given the consumer responses that were collected. These uncertainties were transferred to CIMS such that its modelling results would also reflect uncertainty in consumer behaviour; this information will be relevant and important to decision makers.

In the following section, I first discuss the theory behind discrete choice modelling. Then, I explain the theory behind the CIMS model and how the results from the discrete choice models can be transferred to CIMS. Next, I describe how the uncertainties in the discrete choice models and the CIMS model were characterized. The experimental design is then discussed, followed by a description of the stated preference survey used in the experiment.

2.1 Discrete choice models

Discrete choice models, also referred to as qualitative choice models and Logit models, are a class of models that describe how individual decision makers choose among a discrete set of alternatives. These models interpret consumer decisions as the consumers' perceived importance of the characteristics found in each set of alternatives.

The output of the discrete choice models is the probability that a decision-maker will choose a particular alternative from a set of alternatives, given the consumer behaviours observed by the researcher in a study. This probability output is also synonymous with the predicted new market share of an alternative, because it can be represented as the proportion of consumers choosing one alternative over all others. In this research, the decision makers are passenger vehicle buyers. Hence, the output of the qualitative models discussed in this paper will be the probability that the consumer will choose a particular vehicle from a set of vehicles, given the data solicited through the consumer survey.

Mathematically, discrete choice models define the probability that a consumer n will choose an alternative i from a set of alternatives J (labelled as P_{in}) as dependent on the observed characteristics (z) of alternative i compared with all other alternatives, and on the observed characteristics of the consumer (s_n) (Train 1986):

$$P_{in} = f(z_{in}, z_{jn} \text{ for all } j \text{ in } J_n \text{ and } j \neq i, s_n, B) \quad \text{Equation 1}$$

where j represents possible choices in the set of alternatives J . The observed characteristics are defined by a vector of parameters (B), representing the importance consumers place on each of the characteristics in the alternatives. For example, in a qualitative model of vehicles, the vector of parameters may represent the relative importance consumers place on a vehicle's price, warranty period, and size.

This vector of parameters can be applied to economic theory by representing the relative importance of characteristics as an index of consumer value in units of "utility". Each alternative's total utility can be estimated by using a "utility function", a function that aggregates the utility consumers acquire from each characteristic. The consumer's choice is then assumed to have the highest total utility. However, it is difficult for researchers to predict perfectly what characteristics consumers consider as important in their decisions. Often, researchers can only observe the most common characteristics that consumers feel are important, and build a utility function based on these characteristics. The utility values represented by this function are called the "observable utility", denoted " V ". For example, the observable utility V for vehicle j may be composed of the importance to consumers of vehicle capital cost CC , warranty period W , cruising range CR , and annual fuel cost FC :

$$V_j = B_1(CC) + B_2(W) + B_3(CR) + B_4(FC) \quad \text{Equation 2}$$

where B_1 , B_2 , B_3 and B_4 are weighing coefficients, representing the relative differences in importance that consumers place on each of these four characteristics. This function can be built from consumer choice data through logistic regression, computed by computer software package Limdep 9.0.

The portion of total utility derived from each alternative that is not accounted for in the utility function is called the "unobservable utility", denoted e . This unobservable utility arises from characteristics that consumers feel are important in their decision making process, but that are not observed or considered by the researcher. Nonetheless, this unobservable utility can be accounted by using statistical distributions. Assuming that the unobservable utility can be estimated, a general output formula for discrete choice models can be formulated. Specifically, the probability (P) that a consumer n will choose alternative i over all alternatives J is the probability that the

observed utility (V) and unobserved utility (e) in alternative i is greater than that of all other alternatives:

$$P_{in} = P(V_i + e_i > V_j + e_j \text{ for all } i \text{ in } J) \quad \text{Equation 3}$$

Many different assumptions about the distribution of unobservable utilities can be made, resulting in different discrete choice models (Train, 1985). In this research, the unobservable utility for each alternative is assumed to be distributed independently and identically in accordance with the “extreme value distribution”, which is a distribution observed for many situations, ranging from engineering structures to consumer behaviour (Gumbel, 1954; Rivers, 2003; Horne, 2003; Train, 2003). Qualitative models using this distribution are called “Logit” models. These models express the probability that the decision maker will choose alternative i over all alternatives j as:

$$P_{in} = \frac{e^{V_{in}}}{\sum_{j=1}^J e^{V_{jn}}}, \text{ For all } i \text{ in } J_n \quad \text{Equation 4}$$

For a Logit model with only two alternatives, the Logit function is logarithmic and two-dimensional. An example is a consumer's choice between a HEV and a conventional vehicle as depicted in Figure 1. Note that the change in the utility difference (X-Axis) is identical between each alphabetically labelled point:

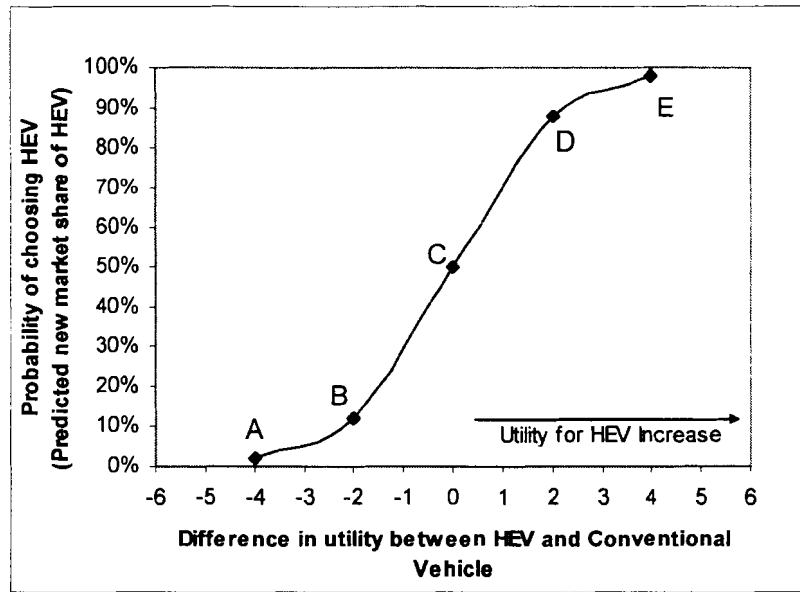


Figure 1 - The Logit model logistic curve

This logistic curve has 3 main properties: (1) as the utility of the HEV increases from point A to point C, the probability of choosing the HEV increases exponentially; (2) where the utility for the HEV is the same as the utility for the conventional vehicle (point C), the probability of choosing the HEV is 50%, such that consumers are indifferent between the two alternatives; and (3) further increases in the utility of the HEV from point C to point E result in diminishing additional probability of the consumer choosing the HEV. Properties (1) and (3) infer that if the difference in utility is large between the two alternatives, the probability value is insensitive to small changes in utility. This is represented by the tail ends of the curve between points A and B, and points D and E. Conversely, if the difference in utility between the two alternatives is small, the probability value is very sensitive to small changes in utility, as represented by the middle of the curve between points B and C, and points C and D.

Although the results of the Logit model can be interpreted on its own, it can also be translated into parameter values for CIMS to facilitate simulations of policy problems requiring realism in modelled consumer behaviour.

2.2 CIMS

CIMS is a hybrid energy-economy model developed by the Energy and Materials Research Group (EMRG) at Simon Fraser University (SFU). It is a “capital vintage model”. That is, it tracks the evolution of capital stocks over time through retirements, retrofits, and new purchases. The model simulates technological change in four inter-dependent steps: (1) calculating the costs for each energy service, such as the cost per person-kilometers-travelled for transportation; (2) retiring capital stocks according to an age-dependent function; (3) calculating market shares for new capital stocks; and (4) simulating inter-sectoral effects by iterating between a macroeconomic component and the energy sectors (supply and demand) until an equilibrium is reached (Jaccard et al., 2003). The energy requirements in step one of the simulation period are directly influenced by consumers’ behaviour in choosing capital equipment through a process called “technology competition”, which is how technologies offering similar services gain or lose new market shares relative to each other in a simulation period.

In CIMS, competing technologies are grouped together into “competition nodes”, where the model simulates the consumer’s processes in choosing among the competing technologies as based on each technology’s “life cycle cost” (LCC), which is a generalized aggregation of costs that consumers owning the technology will incur over the technology’s life. CIMS calculates energy costs by simulating choices of energy-using technologies by consumers and firms at each competition node. Market shares of technologies competing to meet new stock requirements are simulated according to the following equation:

$$MS_j = \frac{\left[CC_j * \frac{r}{1-(1+r)^{-n}} + MC_j + EC_j + i_j \right]^{-v}}{\sum_{k=1}^K \left\{ \left[CC_k * \frac{r}{1-(1+r)^{-n}} + MC_k + EC_k + i_k \right]^{-v} \right\}} \quad \text{Equation 5}$$

Where MS_j is the market share of technology j , CC_j is the capital cost, MC_j is the non-energy maintenance and operation cost, EC_j is the energy cost, i_j is the intangible cost (monetized value reflecting non-monetary decision factors such as option value and consumers' surplus), r is the private discount rate, v is a measure of market heterogeneity and n is the technology's lifespan. The main part of the formula (the part inside the square brackets and summarized in equation 6) is the levelized life cycle cost (LCC) of each technology as seen by consumers and firms. The inverse power function, with v as a key parameter, acts to distribute the penetration of a particular technology j relative to all other technologies k at the node, and is a critical parameter that distinguishes CIMS from a linear programming least cost model (Jaccard et al., 2004). Under a high v parameter, such as $v = 15$, consumers are extremely responsive, such that small changes in relative LCC will lead to wide adoption of one technology while the other technology is abandoned, similar to the behaviour of a linear programming model seeking the least cost solution. Under a low v parameter, such as $v = 1$, consumers are modelled to be less responsive. For new technologies in the transportation sector, the v has previously been estimated to be between 2 and 3 (Horne, 2003).

$$LCC_j = CC_j * \frac{r}{1-(1+r)^{-n}} + MC_j + EC_j + i_j \quad \text{Equation 6}$$

Like the discrete choice model, P_j can be expressed as a proportion and, thus, is synonymous to the predicted market share of technology j (MS_j). The v term is a modifier of the life cycle costs that represents "market heterogeneity", namely, how sensitive consumers are to changes in LCC. For instance, a high v will simulate consumer decisions as highly responsive to the life cycle costs of technologies, such that the technology with the lowest LCC will capture almost all of the new market. Conversely, a low v will represent consumer decisions that are not responsive to the life cycle costs; thus, the new market shares of each technology in the competition node will be similar. For a competition node with only two technologies, the new market share of a technology varies logarithmically with changes in the ratio of LCC. Using the same technology example as in the discrete choice model in the last section but applied to CIMS, the consumer decision for choosing between a HEV and a conventional vehicle is depicted in Figure 2.

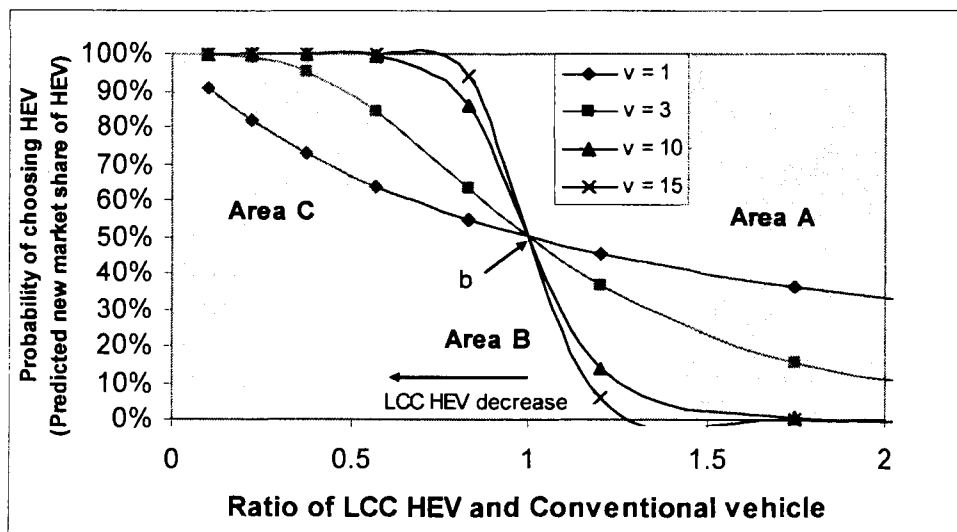


Figure 2 - CIMS logistic curves

This curve has similar properties to the Logit model depicted in Figure 1, specifically:

(1.) The probability of the consumer choosing the HEV increases exponentially as the LCC ratio of HEV and the conventional vehicle declines and is expressed by the curves going from area A to area B. That is, as the LCC of HEV decrease relative to the LCC of conventional vehicles, the probability of consumers choosing HEV becomes higher.

(2.) When the LCC of HEV and conventional vehicles are equal, the result is a ratio of 1 and the probability is 50%. That is, consumers are indifferent between the two technology alternatives (Point b on Figure 2).

(3.) Further decreases in the LCC of HEV relative to the LCC of conventional vehicles achieve diminishing gains in the probability of consumers choosing HEV (Point b to Area C).

When v is of a relatively high value, consumers become not responsive to small relative changes in the LCC of one technology over another where the life cycle cost of one technology is much higher than the other technology (Areas A and C), but are very responsive to small relative changes in the LCC if the LCC of both technologies are similar (Area B).

The variables contributing to the life cycle cost of a technology in equation 6 can be further expanded. In particular, the capital cost and intangible cost of a technology can be defined as dynamic functions in CIMS.

Market data has shown that the capital cost of new technologies usually falls with additional production due to efficiency gains from learning and experience (Wene, 2000; Wene, 1998). In CIMS, this trend is represented by the following function:

$$CC(t) = CC(o) * \left(\frac{N(t)}{N(o)} \right)^{\log_2(PR)} \quad \text{Equation 7}$$

Where $CC(t)$ is the capital cost of the technology during a simulation period, $CC(o)$ is the initial capital cost, $N(t)$ is the stock at the simulation period, $N(o)$ is the initial stock of the technology, and PR is the progress ratio. The progress ratio indicates the gains in efficiency due to learning. The lower the PR , the faster the rate of learning, and the faster the decline in capital cost with each additional unit of production for a technology (Wene 2000; Wene, 1998). For example, a PR of 0.75 indicates a capital cost reduction of 25% for every doubling of production. This ratio for a new technology is usually estimated from historical data in the engineering-economic literature on the relationship between price and the production of similar technologies.

The intangible cost of technologies in CIMS represents the monetized value of decision factors such as option value and consumers' surplus. Historically, the intangible costs are expressed as averages estimated from a combination of literature review, judgement, and meta-analysis (Nyboer, 199; Murphy, 2000). These costs for a new technology may change as a function of the technology's new market share, and affect the technology's competitiveness by contributing to the technology's LCC. The intangible cost of technologies at any simulation period ($I(t)$) is represented in CIMS by the following function:

$$I(t) = \frac{I(o)}{(1 + A * e^{k * NMS(t-1)})} \quad \text{Equation 8}$$

The parameters A and k are scalar parameters, whereas NMS represents the new market share of the technology from the last simulation period. Since this function is

dependent on consumer behaviour towards new technologies, this function can be estimated from consumer data in discrete choice models. In this research, I will build this intangible cost function in CIMS for HEVs from the qualitative models estimated from consumer data collected under different hypothetical market conditions in the stated preference surveys. The results from this intangible cost function will then represent dynamic consumer behaviour towards HEVs as market conditions change through the simulations. Thus, future policy simulation on HEVs in CIMS can incorporate more realistic consumer behaviour rather than simplifying consumer preferences as static and independent of the market.

2.3 Translating discrete choice model results into CIMS

The similarity of the logistic curves in calculating the probability of consumers' adoption of HEVs between the Logit discrete choice model (Figure 1) and the CIMS model (Figure 2) suggests that these two models are comparable to each other. While the discrete choice model is focused on consumer choices based on the relative utility of technologies, CIMS is focused on the relative life cycle cost of technologies. Translating consumer behaviour results from a discrete choice model to the CIMS model requires the following three steps for each technology at the competition node: (1) integrating the relative utilities of non-monetary characteristics of technologies into the intangible cost function in the LCC calculation of each technology; (2) estimating the private discount rates from the discrete choice model; and (3) estimating the variance parameter to determine the responsiveness of consumers to the LCC of the technology alternatives.

2.3.1 Estimating the intangible cost function

The intangible cost function in CIMS is dependent upon 3 main parameters: A , K , and NMS . A and K are variables estimated externally from the model simulations, where

NMS is a variable “endogenous” to the model, that is, the *NMS* variable obtains a value automatically from the model’s internal simulations. To reflect dynamic intangible costs under different market share conditions, *A* and *K* will need to be approximated from each qualitative model based on the market shares of the technology. The process leading to the approximation of these parameters requires four steps. The first step is monetizing the non-monetary parameters from the utility function of the qualitative models. The second step is quantifying the difference in the monetized costs under each market condition for each technology. The third step is converting these costs relative to technologies in CIMS. The fourth step is using the converted costs for each market condition to estimate the *A* and *K* parameters.

Monetization of non-monetary parameters from a utility function involves the use of odds ratios where a non-monetary characteristic in the utility function is valued in terms of a monetary variable, thus the non-monetary variable can be discussed in monetary terms. In this research, the non-monetary parameters are valued by capital cost and thus monetized to a lump sum monetary value:

$$\$i = \frac{B_i}{B_{cc}} * i \quad \text{Equation 9}$$

where $\$i$ is the monetized value of characteristic *i*, B_i is the estimated parameter value for characteristic *i* in the utility function, and B_{cc} is the estimated parameter value for capital cost in the utility function. Note that the parameters B_i and B_{cc} are weighing coefficients in converting their respective attributes into utility, and thus, B_i is in units of utility per *i*, and B_{cc} is in units of utility per \$. Following the example with HEVs in the utility function as depicted by Equation 2, the utility function consists of parameters B_1 (utility per capital cost in \$), B_2 (utility per year of warranty), and B_3 (utility per year of cruising range). Given that the warranty for a particular HEV is 5 years, and the cruising

range is 600km, the following equation monetizes these non-monetary attributes of the HEV to a lump sum monetary value - the total intangible cost:

$$\text{\$Total intangible cost} = \frac{B_2}{B_1} * 5 \text{ years} + \frac{B_3}{B_1} * 600 \text{ Km} \quad \text{Equation 10}$$

After obtaining a monetized intangible cost for each market share condition from the discrete choice models, this cost must be further manipulated to estimate the intangible cost function in CIMS. Since intangible costs are not true monetary costs, they must be treated as relative costs between competing technologies in model simulations, reflecting consumer attitudes. First, the net intangible cost difference between the HEV and conventional gasoline vehicle in each market condition is calculated through subtraction, resulting in a matrix of net intangible cost. Second, a reference intangible cost taken from CIMS is added to this matrix, enabling the intangible costs from this research to be comparable to other technologies in CIMS. An example of this manipulation is presented in Table 2 below. This example follows the previous example with the HEV and conventional vehicle, using hypothetical results that are similar to the findings in my research. The monetized intangible cost of HEV (column A) is subtracted from the monetized intangible costs of the conventional vehicle (column B) for each market scenario, resulting in a matrix of net difference in intangible cost (column C). The net difference in intangible cost (column C) is then added to the CIMS reference intangible cost of conventional gasoline vehicles (Column D), resulting in an adjusted intangible cost of HEV that is comparable to other technologies in CIMS (column E).

		A	B	C	D	E
Utility function #	Market Scenario	Intangible cost of HEV monetized from discrete choice model	Intangible cost of conventional gasoline vehicle monetized from discrete choice model	Net difference in intangible cost	Intangible cost of conventional gasoline vehicle in CIMS	Adjusted intangible cost of HEV
1	0.03% HEV (current scenario)	\$6000	\$1000	\$5000	\$100	\$5100
2	5% HEV	\$5000	\$2000	\$3000	\$100	\$3100
3	10% HEV	\$4000	\$3000	\$1000	\$100	\$1100
4	20% HEV	\$3000	\$4000	-\$1000	\$100	-\$900

Table 2 - Example of a matrix for calculation of adjusted intangible costs for integration into CIMS

Using the information from this matrix, the declining intangible cost function in CIMS (Equation 8) for a technology can be built. The adjusted intangible cost for the current scenario (\$5100 in the example above) is the value associated with $I(0)$, the initial intangible cost variable in the intangible cost function. The market share scenario is NMS , and the respective adjusted intangible costs for each market share scenarios represent $I(t)$ at different times (column E). These relationships can then be used to estimate the A and K parameters for the intangible cost function in CIMS through the use of linear approximation software, such as “solver” in Microsoft Excel.

2.3.2 Estimating the private discount rate

The private discount rate represents the consumers' time preferences on costs. Consumers who express a high discount rate are concerned about the costs in the present more than the costs they may incur in the future. Thus, they place high importance in up-front, lump sum costs, but give less consideration for on-going costs. Consumers who express a low discount rate consider that the on-going costs of a

technology are almost as important as the up-front costs in their purchasing decisions. Translating the discount rate estimated from the utility functions in the discrete choice model to CIMS' r parameter can be done by converting the capital cost to an annualized stream of ongoing costs over the lifespan of the vehicle technology, using an odds-ratio method similar to Equation 9 (Horne, 2003). Using the HEV and conventional vehicle example (Equation 2), the private discount rate can be estimated by the following:

$$r = \frac{B_1}{B_4} \times (1 - (1 + r)^{-n}) \quad \text{Equation 11}$$

where B_1 is the parameter for capital cost, B_4 is the parameter for annual fuel cost (an on going cost), and "n" is the predicted lifespan of the vehicle.

2.3.3 Estimating the variance parameter

Lastly, the variance parameter, v in the CIMS competition node can only be estimated after the LCC if all technology alternatives are estimated. That is, all of the components of LCC, whether they are static or are represented as functions, are defined. This includes the capital cost, discount rate, maintenance cost, energy cost, and intangible costs of each technology in the same competition node.

A major assumption in estimating the v parameter is that that both the CIMS model and the Logit model will predict the same probabilities of consumers choosing one technology over another, or, that these two models will predict the same market shares of technologies. Under this assumption, the Logit model is equated with the CIMS model in technology competition. All variables in both models except for the v parameter in CIMS are solved from data inferred from this research in the prior steps. Thus, v , the

remaining parameter can be approximated using linear approximation software such as “solver” in Microsoft Excel:

$$\text{Logit model} \rightarrow \frac{e^{V_{jn}}}{\sum_{j=1}^J e^{V_{jn}}} = \frac{(LCC_j)^{-\nu}}{\sum_{k=1}^K (LCC_k)^{-\nu}} \leftarrow \text{CIMS model} \quad \text{Equation 12}$$

2.4 Characterizing uncertainty

Decision makers traditionally rely on single estimates from policy models to make management decisions. Often, these decisions are made without an understanding of how reliable the model estimates are, what alternative estimates also exist, and the relative merits of these alternative estimates (Anderson, 1998). Characterizing these uncertainties can help decision makers make better judgements about their actions. Generally, uncertainty is expressed as the “probability” of various outcomes in light of the observed data, or, how likely an outcome will occur given the observations.

In this research, the key sources of uncertainty are in the parameters of the utility functions in the discrete choice models. To make effective use of this research, decision makers must understand other possible combinations of parameters that can be inferred by the observed consumer data, and the degree of belief they should place on the resulting model estimates. Thus, the uncertainties from the discrete choice model parameters must be transferred into the CIMS simulation results. The following subsections will discuss how this process is executed.

2.4.1 Uncertainty in discrete choice model parameters

The Bayesian statistics approach was used in this study to characterize the uncertainty of each parameter in the utility functions of each market condition's discrete choice model. The Bayesian statistics approach has been widely used in decision analysis to characterise the uncertainty of decisions in fields from conservation biology to ecological research (Wade, 2000; Ellison, 1996). This approach assumes that the estimates of each parameter in the utility function are not deterministic (the only answer); instead, these estimates are the centre of a distribution of a range of possible values, for which a probability for each of the values in the distribution can be estimated from the data (Ellison, 1996).

To calculate these aforementioned "Bayesian probabilities" for each parameter, the "likelihoods" of each possible value for each parameter must be calculated; likelihood being an index of how likely that the observed consumer data is true if the parameter estimates are correct. These likelihoods are estimated by the proportion of observed consumer choices from the survey that reflected the "ideal" choice with the highest estimated utility, calculated from utility functions possessing a range of different theoretical parameter values. Theoretically, this range of parameter values is limitless, but for this study I set the limits of this range so the probability of consumer decisions reflecting the "ideal" choice falls below 1%.

In the Bayesian approach, each of the possible values i for each parameter represents a "hypothesis" h_i . The probability of each hypothesis being true, given the observed data ($P_{(h|data)}$), is dependent on a ratio of the products of the "likelihoods" of the observed data:

$$P_{(h_i|data)} = \frac{L_{(data|h_i)}}{\sum_{j=1}^J L_{(data|h_j)}}$$

Equation 13

where J represents all other theoretical values of the parameter in the utility function. In calculating the Bayesian probabilities, I assume that no prior knowledge of the parameters in the utility functions exists. Once the uncertainty in each market share's utility function is characterized, it is used to inform the output of the discrete choice model.

2.4.2 Uncertainty in discrete choice model outputs

The uncertainty in the discrete choice model outputs, namely, the uncertainty in the probability of a consumer choosing one technology over all other alternatives, is derived from the uncertainties in the parameters of the utility function. This can be characterized using a "Monte Carlo simulation".

In a Monte Carlo simulation, the computer repeatedly samples parameter values according to a probability distribution then inputs each parameter value into the intended function to calculate a distribution of the output. Often, the sampling is repeated thousands of times to create a smooth output distribution. For the purpose of defining the uncertainty in the discrete choice model output, the computer builds variations of the utility function by repeatedly sampling parameter values according to their Bayesian probabilities, with a total coefficient deviation range of +/-20% for each parameter. I imposed this limitation on the deviation range because I feel that using a narrower range will better represent real consumer preferences than using the full Bayesian distribution for each coefficient as mention in the previous section. For example, a positive coefficient for the capital cost attribute may be possible under a Bayesian distribution as

defined in the previous section. However, this is highly unlikely in the real world. Narrowing this range also allows the uncertainty in the discrete choice model outputs to be characterized with higher resolution. Using the utility functions with the various coefficient estimates for all attributes, a distribution of discrete choice modelling outputs is created. This distribution can then be summarized using a bar graph (a histogram) representing a probability distribution of the likelihood consumers will chose HEVs over conventional vehicles, or a probability distribution of the range of possible predicted market share of HEVs for a given market condition. Analysts can then use these graphs to determine their degree of belief in the outputs from the discrete choice models.

2.4.3 Translating uncertainty into CIMS

To make use of the uncertainty information from the discrete choice model for policy simulations, the uncertainty from the discrete choice model output is translated into CIMS by way of two parameters in the life cycle cost of technologies (equation 6): the discount rate, r , and the intangible cost function, i . In its current state, CIMS cannot input a distribution of parameter estimates attached with probabilities. Thus, I expressed the uncertainty of the CIMS outputs as a sensitivity analysis. That is, I estimated various simulation outputs from the CIMS model by inputting r and i parameters that encompassed the range of possible values.

To characterize the uncertainty in CIMS outputs due to the uncertainty in the discount rate, a Bayesian probability distribution of possible r 's is calculated from a distribution of capital cost and fuel cost parameters in the discrete choice model. The end points of this distribution are defined as the probabilities where r has fallen below 1%. These two endpoints are input into two separate simulations in CIMS to indicate the range of possible CIMS outputs due to the uncertainty in r .

A similar approach is used to characterize the uncertainty in the intangible cost function, i , in CIMS. The end-points that encompass the range of the i distribution are estimated from the highest and lowest i that can take place. This is accomplished by first finding the two combinations of non-monetary parameters in the discrete choice utility functions that will likely produce the highest utility and the lowest utility, given their respective Bayesian probabilities. Then, these two utility functions representing the ends of the i distribution are translated into two sets of A and K parameters to generate their respective CIMS intangible cost functions. The simulation results from these intangible functions then indicate the range of possible CIMS outputs due to the uncertainty in intangible cost.

2.5 Experimental design

The consumer choice experiment is a critical component in this research. It collects the data that is required to build the discrete choice models, which will show how consumers' values of the characteristics of HEVs are affected by market conditions. The experimental outcomes must include data to support the three requirements in building discrete choice models for each market condition: (1) a list of alternative technologies, (2) a list of the most commonly valued characteristics, or "attributes" of these alternatives, and (3) a record of consumer choices. The experimental design is outlined in Figure 3. It will be described in detail in the subsections that follow.

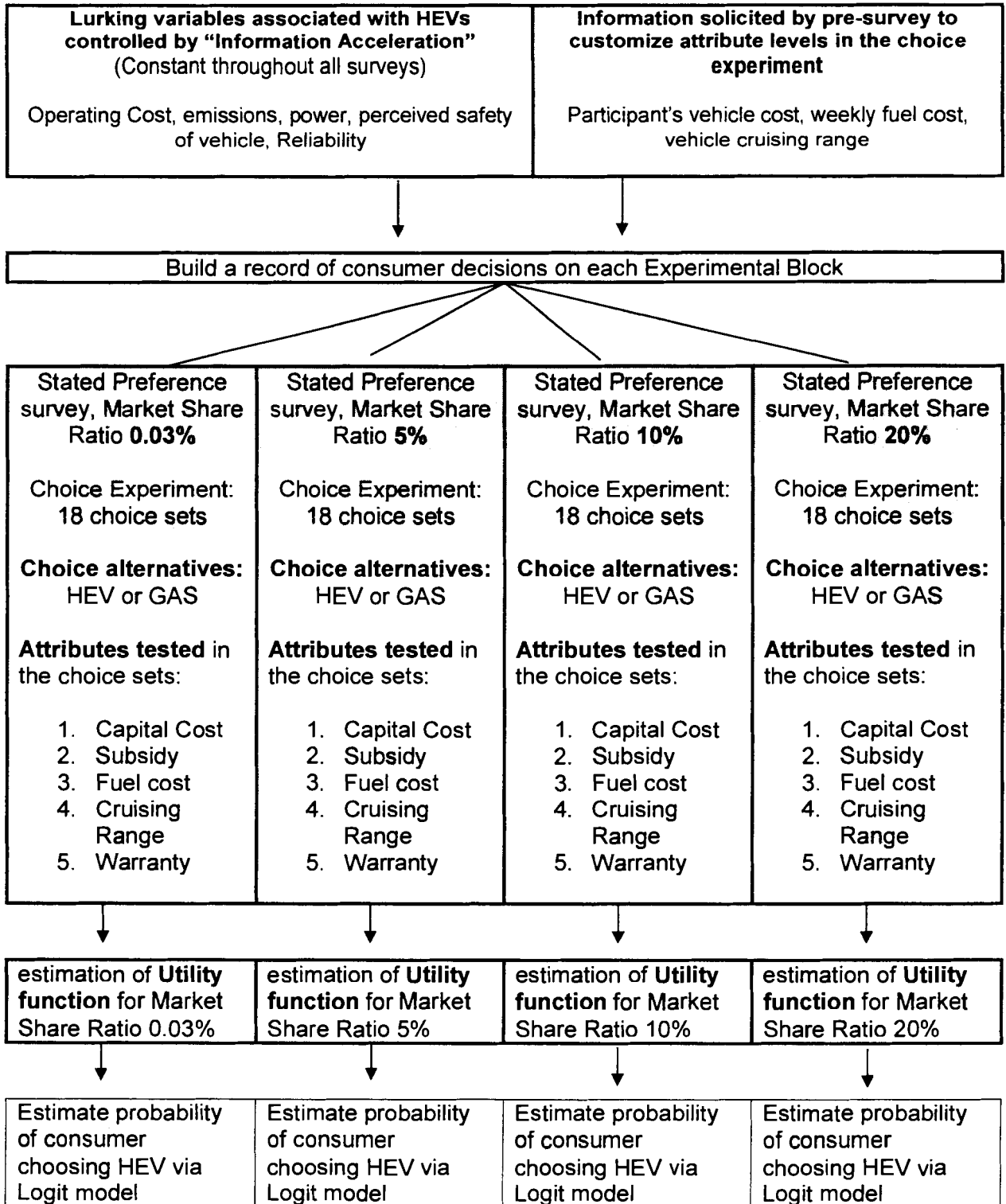


Figure 3 - Experimental Design Flow Diagram

2.5.1 Determining the list of alternatives

In the experimental design, the list of alternative technologies was generalized into two technologies from which consumers could choose either HEVs or conventional gasoline vehicles. All other vehicle technologies, such as electric vehicles, were excluded because they have an insignificant market share in CIMS relative to conventional gasoline vehicles. In addition, offering two technologies simplifies the modelling process and enables higher precision by allowing more characteristics to be modelled.

2.5.2 Obtaining the list of attributes

Vehicular attributes most commonly valued by consumers were obtained from a search of past transportation research (Horne, 2003; Brownstone et al., 2000; Ewing & Sarigollu, 2000; Brownstone & Train, 1999; Bunch et al., 1993). Although the literature presented a long list of potentially important attributes, only five attributes were chosen for this experiment in order to maintain data quality and to present a choice experiment of reasonable size (Montgomery, 1997). These five attributes include capital cost, fuel cost, cruising range, government subsidy, and warranty period, which became the basis for the utility function in the Logit model:

$$U_j = B_1(CC) + B_2(FC) + B_3(S) + B_4(CR) + B_5(W) + B_{ASC} + e \quad \text{Equation 14}$$

Where B_1 is the parameter for capital cost (CC), B_2 is the parameter for fuel cost (FC), B_3 is the parameter for subsidy (S), B_4 is the parameter for cruising range (CR), B_5 is the parameter for warranty (W) and B_{ASC} is the "Alternative Specific Constant", which captures all other characteristics unique to technology i . It is assumed that the error term e of the total utility of technology U_i is distributed according to the extreme value distribution.

2.5.3 Obtaining the record of consumer choices

The record of consumer choices based on the utility function in equation 13 had to be solicited through a discrete choice stated preference survey, because there was no prior market history of consumer decisions between HEVs and conventional gasoline vehicles based on the attributes investigated by this research. In order to capture a variation of responses, consumers were asked to choose between a HEV and a conventional gasoline vehicle through a variety of different "choice sets", which are different combinations of levels of attributes for each vehicle. Figure 4 illustrates a sample of such a choice set.

<i>If these were the only vehicle options available to you, which one would you choose?</i>		
	Gasoline Vehicle	Hybrid Electric Vehicle
Days you can use the car between refuelling	5	6
Fuel Cost / Week	\$38	\$25
Purchase Price	\$17,600	\$28,500
Warranty Coverage Period	5 years	10 years
Subsidy on Purchase Price	No Subsidy	\$3200
I will choose: (Check one)	<input type="checkbox"/>	<input type="checkbox"/>

Figure 4 - a sample choice set

Each vehicle attribute had three levels: low, medium, and high. These levels were represented in the choice sets as numeric values relative to the survey participant's current vehicle because it was thought that if participants were presented with levels of vehicle characteristics that they could not relate to, they could get confused and possibly

make inconsistent choices. (Whitehead, 2002; Herriges et al., 1996; Boyle, 1985). The variations of levels of each attribute are presented in Table 3 below:

		Attribute Level - relative to the attributes of the participant's current vehicle		
Attribute	Vehicle Technology	Low	Medium	High
Capital Cost	Conventional	User _{cc}	User _{cc} * 110%	User _{cc} * 120%
	HEV	User _{cc} * 140%	User _{cc} * 170%	User _{cc} * 190%
Fuel Cost	Conventional	User _{fc}	User _{fc} * 110%	User _{fc} * 125%
	HEV	User _{fc} * <i>k</i>	User _{fc} * <i>k</i> * 110%	User _{fc} * <i>k</i> * 125%
Subsidy	Conventional	None	None	None
	HEV	5% of HEV price	10% of HEV price	20% of HEV price
Cruising Range	Conventional	User _{cr}	User _{cr}	User _{cr}
	HEV	User _{cr} * 120%	User _{cr} * 150%	User _{cr} * 200%
Warranty	Conventional	5 years	5 years	5 years
	HEV	5 years	8 years	10 years

Table 3 - Attribute levels in the vehicle choice experiment

User_{cc} is the capital cost of the survey participant's vehicle, User_{fc} is the amount of money the survey participant would spend on fuel each week, and User_{cr} is the range in km or the number of days the survey participants' vehicle could be driven on a full tank of gas. Since HEVs have a higher cruising range than conventional vehicles, the variable *k* denotes the adjustment ratio for higher fuel efficiency. Thus, if the HEVs have 200% higher cruising range than the conventional vehicle, *k* would be 0.5, which would reduce the fuel cost by half.

Presenting the participant with all the choice sets that can be created from every combination of the attributes and levels would generate an ideal record of consumer responses from the stated preference survey. That is, the survey has a “full factorial design”. Such a survey would include 3^6 , or 729 choice sets. However, participants will not be able to realistically complete such a task. Hensher et al. (2001) found that the quality of the answers from choice experiments starts to deteriorate after the 30th choice set either due to the participant’s loss of interest or fatigue. Thus, full factorial designs are rarely used in stated preference discrete choice experiments. Rather, most investigators use a “fractional factorial design”, namely, a design that represents each level of each attribute enough times to document its individual effects, while assuming that the attributes do not interact with each other (Montgomery, 1997). The fractional factorial design is seen in design plans for discrete choice models previously built for CIMS on subjects ranging from co-generation (Rivers, 2003) to transportation mode choice (Horne, 2003). For this experiment, I chose to build the survey with a fractional factorial design of 18 choice sets, representing the three levels of each of my five attributes enough times to document their individual effects on consumer decisions without interactions between attributes. The full design plan is presented in Appendix III.

Soliciting consumer choices with this design plan will provide enough data to build a linear utility function from logistic regression, a technique handled by the computer software package Limdep. However, this utility function does not account for consumer responses to HEVs under different market conditions. To specify these responses, individual utility functions must be built from different consumer surveys representing different market conditions. These utility functions of each market condition are then compared to each other to observe consumer behavioural trends between market shares.

2.5.4 Accounting for market conditions

Characterizing how consumers' decisions towards HEVs change with different market conditions was a major innovation for this type of research. Of interest in this study were four market conditions, namely, four market shares of HEVs: 0.03%, 5%, 10%, and 20%. These four market share conditions were studied because policy makers will gain the most from understanding consumer behaviour in the initial stage of technology introduction, and because they spanned an appropriate range of market share conditions that describes most changes in consumer behaviours. After a technology has gained a significant market share, it will gain its own momentum and will no longer require much assistance from policy. In the field of Marketing, the market share ratios between 0 and 20% are dominated by the "innovators" and "early adopters". These are the consumer groups that are first motivated to take up a new technology. As a result of technology uptake by these two groups, the reluctance of more conservative consumers may decline (Mahajan et al., 1990).

In the consumer choice experiment, the market shares of HEVs were represented as "market share ratios", which are ratios of HEVs to conventional gasoline vehicles. This approach was used because it can approximate the actual market share of HEVs, and it simplifies the language in the survey for participants. A detailed appraisal of what these market share ratios represent in terms of the absolute number of HEVs in Canada is presented in Table 4. These market share ratios have been developed in conjunction with a complimentary study on disruptive technologies (Eyzaguirre, in progress) Therefore in the future my results on evolutionary technologies can be directly compared with results from the study on disruptive technologies, and draw inferences on consumer behaviour between the two technology categories.

Market Share Group (representing the experimental blocks by market share ratio)	Total Annual Vehicle Sales in 2003	Sales - Conventional Vehicle	Sales - HEV
Group 1* - Current market condition for HEVs (2003)			
	1,703,511	1,703,063	448
Market share of each technology as a percentage of new sales of all vehicles		99.97%	0.03%
Market share ratio of HEVs to Conventional vehicles			0.03%
Group 2*			
	1,703,511	1,620,511	83,000
Market share of each technology as a percentage of new sales		95.13%	5.12%
Market share ratio of HEVs to Conventional vehicles			5%
Group 3*			
	1,703,511	1,560,511	143,000
Market share of each technology as a percentage of new sales		91.61%	9.16%
Market share ratio of HEVs to Conventional vehicles			10%
Group 4*			
	1,703,511	1,454,911	248,600
Market share of each technology as a percentage of new sales		85.41%	17.09%
Market share ratio of HEVs to Conventional vehicles			20%
<i>* the market share groups in this study have been developed in conjunction with a complementary study on disruptive technology by Eyzaguirre (in progress) such that both studies can be directly compared.</i>			

Table 4 - Experimental Blocks. Data from Autonews (2003)

Accounting for the four market conditions required the estimation of four qualitative models from four utility functions. Each of the four utility functions of each market condition were comparable to each other such that a relationship between them

could be identified. They were all derived from the same set of alternatives (HEV or conventional gasoline), and had the same set of attributes (capital cost, fuel cost, subsidy, cruising range, warranty). Hence, the probability of consumers choosing one alternative over the others could be estimated independently for each respective market condition. The experimental design accommodated for this by treating the market share ratio as a blocking variable, and then separating the sample population into four “market share groups”. Each market share group was then assigned a different version of a stated preference survey reflective of their market share ratio.

Most components of the four versions of stated preference surveys were designed to be identical, including the attributes and levels in the choice sets. The key difference between the four surveys was the portrayal of the market share conditions. Although traditional stated preference surveys educate participants through conceptual descriptions, this survey took an innovative step called “information acceleration” to facilitate this process by actively engaging participants in learning about their assigned market conditions.

2.5.5 Information acceleration

Consumers usually become informed about new products gradually over time, through processes such as talking to friends, visiting a show room, or reading articles in the newspaper. Reproducing these experiences through hypothetical situations in a survey are valuable because participants can gain a better understanding than they would from conceptual descriptions. For instance, due to advancing computer multimedia technology, these experiences can be manipulated, then easily created and delivered to survey participants in a very short period (Peterson et al., 1997).

Marketing firms use information acceleration to inform consumers of new products. For example, electric vehicles have been marketed by creating a virtual showroom, and cameras have been marketed by reproducing television advertising, simulating word-of-mouth communications, and showing consumer magazine articles on the computer (Urban et al., 1996). Information acceleration has also been used to inform medical professionals of new medical instruments by reproducing virtual face-to-face interactions with physician colleagues, medical technicians, and salespeople. In most of these cases, information acceleration can quickly reproduce consumer experiences that are comparable to those in real-life (Urban et al 1997).

In this research on HEVs, I used information acceleration to (1) introduce the concept of HEVs to the survey participants, (2) control “lurking variables” - variables that consumers may consider, but are not included in the choice experiment, and (3) inform participants about their hypothetical market condition. The reproduction of experiences associated with each of these three points are delivered through an online website (Figure 5), where users can browse through a brochure (Figure 6) and receive virtual appraisals of HEVs stated by different people (Figure 7).

Section 3: Information on Hybrid Electric Vehicles

This section illustrates a hypothetical scenario where *1 out of every 5 vehicles sold last year were hybrid electric vehicles*. The sources below contain information about this hypothetical setting.

Please take the time to read the brochure and at least two of the personal statements below. Feel free to browse for as long as you like. Immerse yourself into this hypothetical setting to the best of your ability.

This section sets the stage for the next one.

The links below will open up new windows.

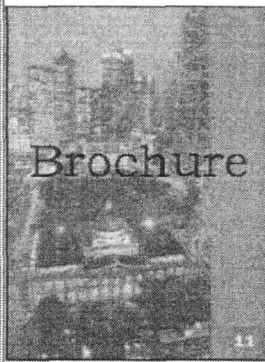





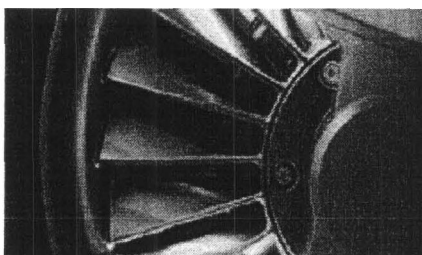
	Personal Statements				
	 "I don't make major purchases without consulting Consumer Reports."	 "When it comes to vehicles, we are not willing to sacrifice comfort and convenience."	 "My best friend drives a hybrid electric vehicle. She says it performs just as well if not better than her previous gasoline car. I'm thinking about switching myself."	 "I waited until I saw several hybrid electric vehicles on the road and in dealerships before I bought one."	 "I have the need for speed!"

Figure 5 - Information Acceleration web page

Powered by an advanced system that combines an ultra-efficient gasoline engine with a battery-powered electric motor, hybrid electric vehicles have all the performance of conventional cars while running much cleaner. And that's not all .



PERFORMANCE The gasoline / electric hybrid engine provides powerful and smooth acceleration when you need it most: from starting up to climbing hills.

When coasting or applying the brakes, the battery-powered electric motor actually becomes a generator, recharging as you drive by converting forward momentum into electrical energy. The energy is stored in the system's Nickel Metal Hydride (NiMH) battery pack and re-used to assist the gasoline engine when you accelerate.

Figure 6 - Example of a brochure used in Information Acceleration

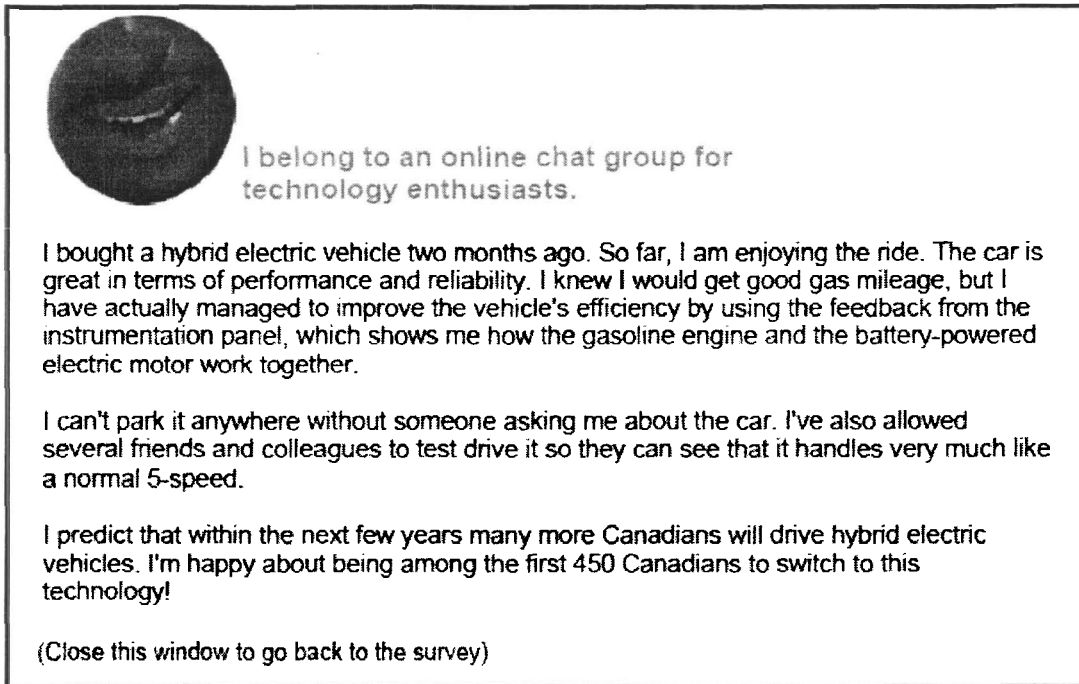


Figure 7 - example of a virtual appraisal (Personal Statement)

The experiences associated with introducing the concept of HEVs were represented by the virtual magazine article describing the basic technical specifications of a HEV, followed by three positive personal appraisals and two negative personal appraisals aimed at duplicating personal driving experiences. Magazine articles outlined the experiences associated with lurking variables such as expectations about HEV performance, efficiency, safety, and convenience. In this research, the information acceleration content associated with introducing the concept of HEVs and controlling the lurking variables were identical across all four versions of the survey to maintain consistency. The experiences associated with informing participants about their hypothetical market conditions were described through different repeated colloquial descriptions on the website, and also through descriptions in the brochure and the personal appraisals. These descriptions about hypothetical market conditions are the key to informing participants about their assigned market condition, and are the key

difference between the four versions of the survey. Translation of the market share ratio into colloquial terms, such as “I’m among the first 450 Canadians to get a HEV” and “500 of the 1.5 million vehicles sold last year were HEVs” was necessary because the survey participants may get confused if the market share concepts are presented in mathematical ratios (Ahearne, 1993).

2.6 Stated preference online survey

The online survey supports the experimental design by collecting consumer choice decisions between HEVs and conventional vehicles under different hypothetical market conditions. The execution of the survey has three components. The first step is determining a sample population to be surveyed. The second step is determining a how many participants will be surveyed (sample size). The third step is conducting an online survey to solicit response. These components will be discussed in the following sub sections.

2.6.1 Sample population

The sample population was carefully chosen to accurately represent choice decisions about HEVs and conventional vehicles for Canadian consumers that can be targeted by future environmental policies on clean vehicles. The sample population also needed to be knowledgeable about the costs of gasoline vehicles, understand the purchasing process, and understand the everyday “hassles” associated with vehicles, such as the inconvenience of fill-ups and maintenance. Thus, the sample population consisted of Canadian residents over 19 years of age, who commute at least once a week, currently own a conventional gasoline vehicle, and live in urban centers with a population greater than 150,000 people.

To gain access to a sample population, I hired a marketing firm. Two options were considered: random telephone solicitation and an internet online panel. After experiencing a very low response rate from the telephone solicitation, I turned to the internet online panel option, which is a group of volunteers who have agreed to complete internet surveys out of interest and in exchange for potential prizes. This panel consists of 50,000 members, and represents the population distribution of Canada. Participants in my research sample completed a screening questionnaire (see Appendix I) to verify their eligibility with respect to belonging to my target population.

2.6.2 Sample size

Traditionally, the sample size of experiments can be determined through a formal statistical analysis called “power analysis” such that the sample size will have a high degree of reliability in supporting or refuting a research hypothesis (Schwartz, 2004). Although this can be easily done for continuous choice models, my research involves discrete choices from the sample population. Unfortunately, a formal power analysis procedure on this type of experimental design is not well established. Hence, I determined the minimum sampling size through a computer simulation of randomly selected virtual participants completing the choice experiment questions. The number of completed virtual responses required to estimate parameters in the utility function that are significant at the 0.10 level became my minimum sample size, namely, 100 for each of the market share blocks for a total of 400 completed responses. To ensure a complete sample, I requested double the minimum size from the online panel, which is 200 completed surveys in each market share block, for a total of 800 completed surveys.

2.6.3 Conducting the online survey

Through the online survey, data was collected regarding consumer decisions in selecting between HEVs and conventional gasoline vehicles under different attribute levels at each of the four market conditions. There were four parts in this survey. The first part collected information about the characteristics of the vehicle that the survey participants currently own and the participant's driving habits. This information was used for customising the baseline of alternatives in the discrete choice experiment. The second part was information acceleration, where participants learned about the HEVs and were prepared for the discrete choice experiment. Part three of the survey was the discrete choice experiment, where participants chose between the HEV and the conventional vehicle under 18 different sets of attribute levels, which were presented one set at a time. The record of consumer decisions from this section of the survey was collected for analysis. The last section of the survey collected personal participant information such as demographic data and their attitude toward new technologies. The results from this section verified each participant's eligibility in the survey, and also can be used for future analysis into how consumers choose based on personal characteristics. The complete survey is presented in Appendix II.

Since the survey was delivered online, many technical aspects of the survey could be controlled to maintain the quality of the data. The first technical aspect was input error prevention. The participant chose responses from drop down lists or selection buttons such that the responses could be standardized. The second technical aspect was preventing strategic bias, namely, participants deliberately changing their responses after the survey to reflect what they wish for instead of reflecting their true preferences, thereby skewing the data. The computer controls the strategic bias by blocking changes to answers once participants have submitted their responses.

Randomizing the question and attribute orders within the survey prevented “hypnosis”, where participants become fixated on the first few attributes in each choice set due to repetitive questioning. This randomization also ensured that all questions were well represented, and were answered with equal frequency. Market share block assignment was done sequentially on the order participants were solicited, such that all blocks will have a similar population size. Participants were also prevented from repeating the survey, or submitting multiple surveys through a secured login system where each participant was given a unique ID and password which expired automatically after one use.

3 RESULTS

By using the qualitative models that are built from the data collected in the stated preference survey, consumers' behaviours towards HEVs can be characterized. This chapter includes an analysis of the survey data, presents the resulting discrete choice models, and reports on the CIMS parameter estimates. The first section comments on the representativeness of the survey sample population. The second section discusses on the quality of responses from the survey participants. The third section compares and contrasts the discrete choice models synthesized from the choice experiment results. The fourth section discusses the CIMS parameters obtained from the discrete choice models. The fifth section discusses the uncertainties in both the qualitative modelling results and the CIMS modelling results.

3.1 Sample population

The sample population, sometimes called the "survey sample", refers to the group of people who have participated in the stated preference survey. In this study, the data obtained from the sample population was used to draw inferences about the "target population", namely, the potential vehicle consumers in Canada.

To make useful inferences, it is important that the preferences reflected by the survey sample represent those expressed by the target population. Indeed, my analysis of the sample population shows that the information on consumer preferences obtained from this research is representative of the behaviours expressed in the target population. I determined the representativeness of the survey sample based on two factors: (1) statistical precision, and (2) the sample's demographic characteristics. The size of the

survey sample determines statistical precision. Generally, the larger the survey sample, the greater the likelihood of being able to draw more precise inferences from the target population. After the surveying phase of the study was complete, the data showed that 1262 participants met the participation criteria, and 916 of them completed the survey. All four “market share blocks” received at least 200 completed sets of responses. Thus, the predetermined sample size was satisfied (Figure 8).

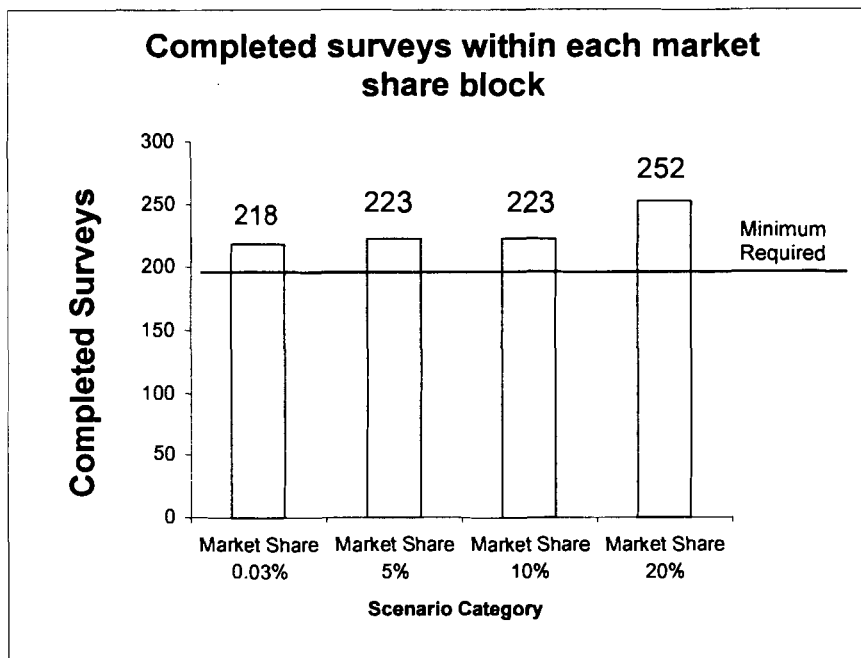


Figure 8 - Completed responses in each sample block

Demographic representation of the survey sample is how well the personal characteristics and geographical distribution of the sample population matches the target population. Proper demographic representation ensures that the results are not skewed towards the views of only a select group of people. The regional distribution of the participants matched that of Canadians in household income, age, and household size for the year 2002 as illustrated in Figure 9 (Statscan 2002). The only discrepancy was in gender distribution. While the Canadian population has about an equal number of males

and females, 67% of the participants in this survey were female. However, statistical testing revealed that there was no significant difference in consumer behaviour between males and females in this study.

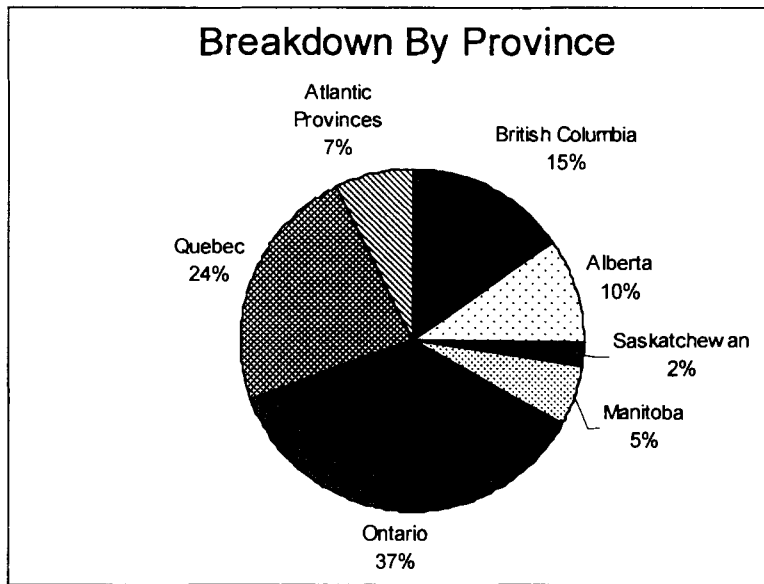


Figure 9 - Regional distribution of participants

Upon inspection of my survey sample, a majority of the participants were owners of passenger vehicles (cars, Mini-Vans, and SUV's), rather than owners of larger vehicles more associated with transportation of goods such as trucks (Figure 10). A recent study by the British Columbia Automobile Association (BCAA) has found that over 86% of vehicle owners would repurchase the same vehicle type again if given the chance in the future (BCAA 2004). Therefore, the sample population's current vehicle ownership is a good predictor of potential consumer behaviour towards their next vehicle of the same vehicle type. Thus, the results of this research can be generalized and be applicable to modelling the behaviour of passenger vehicle owners.

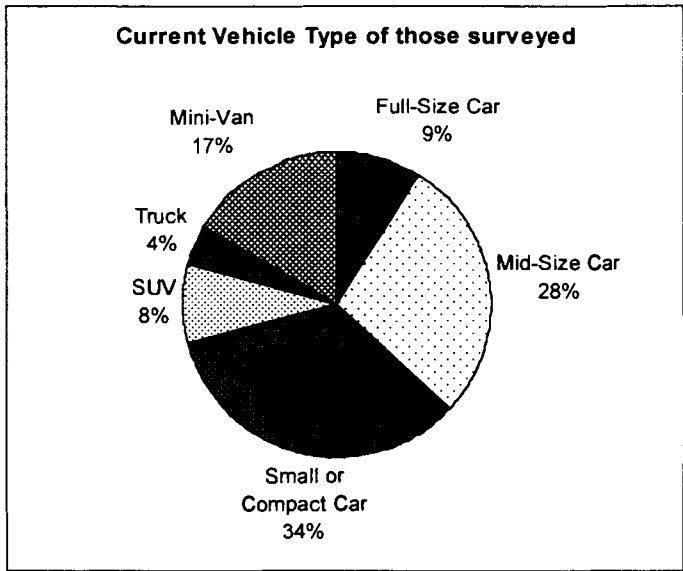


Figure 10 - Vehicle type distribution of participants

Finally, the sample population’s distribution of consumer adoption categories may affect the applicability of this research. Consumer adoption categories represent the willingness of consumers to adopt new technologies, ranging from “innovators” - those who have a high affinity for purchasing new technologies, to “early majority”, those who follow the lead of innovators, to “laggards”, those who are reluctant to adopt any new technologies. People in the “early majority” consumer category tend to purchase new technologies under low market share conditions. Hence, it is important to capture the consumer behaviour of this consumer group. The consumer adoption categories of survey participants are inferred from responses in the survey questions, and the results indeed indicate that most participants belong to “early majority” (Figure 11). Thus the data collected in this study are relevant to my research’s target population.

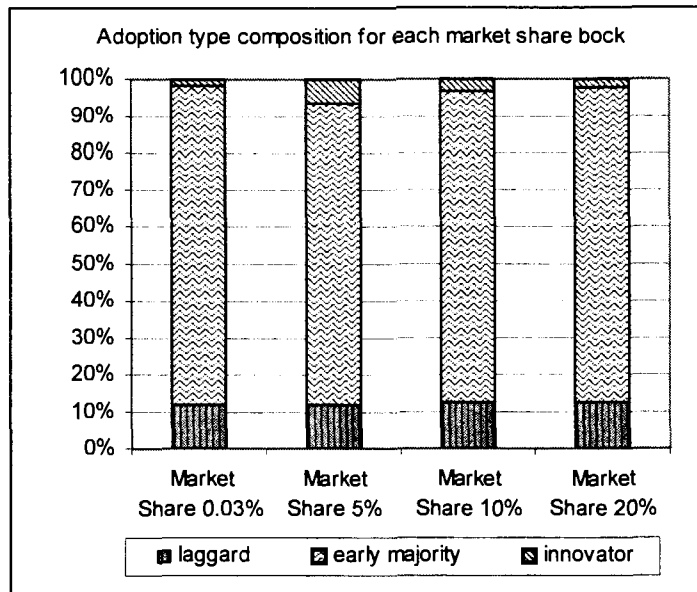


Figure 11 - distribution of consumer adoption groups in each market share

Overall, the analysis of the sample population suggests that the results from the survey adequately represent the target population under study. Next, I will evaluate the quality of the data collected from this sample.

3.2 Quality of responses

To estimate discrete choice models that provide useful information, consumers must find importance in the choice experiment's attributes. If the survey participants do not find these attributes to be important in their decisions, or if they do not express interest in evaluating them in the survey, then the resulting models would not be informative. To assess the quality of the data submitted by the survey participants, I used three indicators.

The first indicator of quality is the frequency distribution of respondents who make the same technology choice for all questions in the choice experiment (ie. only choosing HEVs regardless of the question). If the participants consistently chose one technology over the other, then the quality of the data would be unsatisfactory. This

outcome could mean that either the participants felt the attributes were not important, or, the participants made a decision prior to the survey to choose one vehicle technology over the other. Either of these situations could indicate that the participants were not considering the presented questions and attributes carefully. In my survey sample, the proportion of participants that consistently chose one technology over another was low relative to all the collected data, ranging from 9% to 20%. Thus, the distribution of responses was adequate. This result indicates that most participants considered the questions carefully, and that the attributes indicated in the choice experiments were important to most people in their decision process.

The second indicator of quality is the point of departure for participants who did not complete the choice experiment. Although results from incomplete surveys were discarded, the understanding of where the participants quit can lead to insights into any potential bias. For example, if the participants tended to quit in choice sets where the fuel cost attribute is high, then that could indicate protests against high fuel costs. I assessed 346 incomplete surveys and found that participants quit the survey at all points during the 18 discrete choice questions. There is little indication that participants collectively protested against a particular section of the survey. Similarly, it is unlikely that participants deliberately biased the survey results.

The third indicator of quality is the distribution of participants' choices across the 18 choice sets. If the survey participants all chose HEVs 50% of the time, then that would indicate that (1) the participants were choosing their responses at random; (2) the attribute levels failed to define a distinct difference in the technology choices; or (3) the attributes were not important enough to the participants' decisions to be considered carefully. In all three of these cases, the qualitative model derived from such patterns of consumer data will not be useful or informative. Figure 12 summarizes the distribution

pattern of the participants' choices, and it shows that the respondents were cohesive in finding enough differences among the attributes presented in the choice sets to make distinct choices. Hence, the attributes presented in the choice experiment were influencing the participant's decisions.

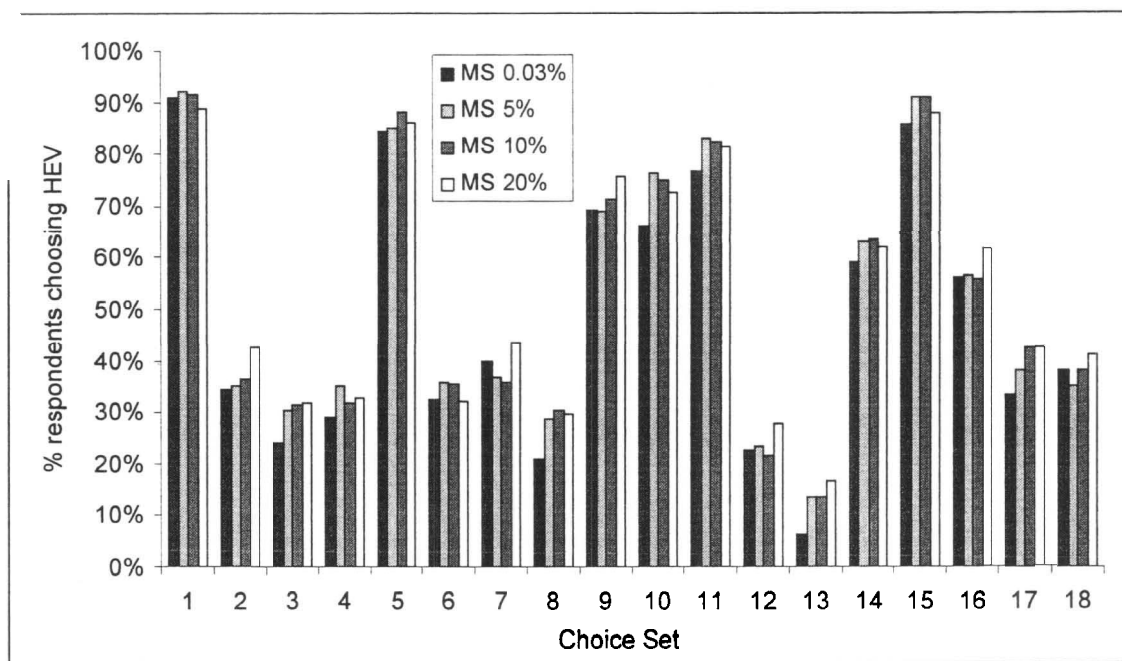


Figure 12 - Frequency distribution of HEV being chosen for each choice set. Variation in frequencies between choice sets indicates participants' decisions are influenced by the attributes presented.

Overall, the quality of responses from the choice experiment in the survey is satisfactory. The participants found the attributes that distinguished HEVs from conventional gasoline vehicles to be important; the majority of the participants considered each choice set carefully; and the data indicate that their decisions were influenced by the attributes that I have included in the choice experiment. Thus, the discrete choice models developed from my results had a high potential to draw informative inferences about the target population.

3.3 Experimental results and analysis

I used the results of the choice experiment to answer my three research questions:

- (1.) Do people place different values in the attributes of HEVs and conventional vehicles?
- (2.) If so, how do these values change with changing market conditions?
- (3.) What do these results suggest for policymaking?

I will answer the first question by using the experimental data to build discrete choice models for each market condition, then analyze each of these models independently. I will answer the second question by comparing the discrete choice models for each market condition. I will answer the third question by aggregating the results from the discrete choice models and then translating them to parameters in CIMS, in order to conduct a series of policy simulations. Each of these components will be discussed in the sections below.

3.3.1 Discrete choice models

I developed four discrete choice models in total, one for each market share block, from the set of consumer decisions collected in the discrete choice experiment. With the consumer data, I estimated the parameters or, "coefficients" for each attribute using the logistic regression statistical package Limdep 9.0. The coefficients captured the relative importance consumers place on each of the attributes, namely, the higher the magnitude of an attribute's coefficient relative to others, the higher the importance placed by consumers on a one unit increase in that attribute. These coefficients for each market share block are presented in Table 5 below.

Attribute	Market Share Block 0.03%		Market Share Block 5%		Market Share Block 10%		Market Share Block 20%	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
<i>Capital Cost</i>	-1.95E-04	< 0.0001	-1.64E-04	< 0.0001	-2.37E-04	< 0.0001	-1.79E-04	< 0.0001
<i>Fuel Cost</i>	-4.12E-02	< 0.0001	-2.64E-02	< 0.0001	-3.37E-02	< 0.0001	-1.68E-02	< 0.0001
<i>Subsidy</i>	2.90E-04	< 0.0001	3.06E-04	< 0.0001	3.49E-04	< 0.0001	2.99E-04	< 0.0001
<i>Cruising Range</i>	7.91E-02	< 0.0001	5.73E-02	< 0.0001	6.55E-02	< 0.0001	2.69E-02	8.10E-05
<i>Warranty</i>	1.66E-01	< 0.0001	1.09E-01	< 0.0001	1.24E-01	< 0.0001	1.17E-01	< 0.0001
<i>Alt. Specific Constant for gasoline vehicles</i>	2.02E-01	3.78E-02	-8.56E-02	3.32E-01	-3.72E-01	< 0.0001	-5.01E-01	< 0.0001
Number of choice observations	4338		4518		4608		5022	
Log Likelihood Function (Full)	-2409		-2641		-2468		-2931	
Log Likelihood Function (No coefficients)	-3006		-3131		-3194		-3480	
Log Likelihood Function (Alternative Specific constant only)	-3005		-3127		-3190		-3467	
Log likelihood ratio	0.20		0.16		0.23		0.16	

Table 5 - Discrete choice models

3.3.1.1 Validity of models

Before making comparisons among coefficients for different models and drawing inferences from them, it is important to assess the validity of the models. This includes (1) checking whether the coefficients have the correct sign; (2) testing the statistical significance of each coefficient; (3) assessing how well the model fits the data set through log likelihood ratios; (4) assessing the influence of the alternative specific

constants (ASCs) on the models; and (5) assessing whether the coefficients associated with the non-monetary attributes are plausible by converting them into monetary equivalents.

Assessing whether the coefficients have the correct “sign” offers a simple validity test. The expectation is that desirable characteristics should have a positive coefficient because they increase utility, whereas undesirable characteristics should have a negative coefficient because they decrease utility. Table 5 shows that the coefficients all have the expected signs. Increases in the attributes associated with costs are undesirable. Thus, increases in capital cost and fuel cost lead to a decrease in utility, and this was confirmed by negative coefficients in these parameters. Increases in attributes associated with benefits are desirable. Thus, higher subsidies, cruising range, and extensions in warranty can lead to additional utility, and this was confirmed by positive coefficients in these parameters.

The statistical significance of each attribute coefficient indicates the probability that consumers ignored the attribute in their vehicle decisions. This probability was denoted as the “p-value” for each attribute, which ranges from 0 to 1. Attributes that have coefficients with small p-values are unlikely to be ignored, and thus they are “significant” in informing the qualitative models. Conversely, attributes with high p-values indicate that the consumer likely ignored them, and, thus, these attributes are usually taken out of the model. In this research, the threshold p-value in defining “significant” attributes was 1%. In Table 5, the p-values of all coefficients in each qualitative model meet this threshold, namely, all the attributes are statistically significant. In sum, all five attributes are significant, indicating consumers likely found all five attributes to be important in their vehicle purchase decisions.

Table 5 above also shows the predictive capacity of the qualitative models through the log likelihood ratio index. This index is commonly used to assess the “goodness of fit” of the models to their respective data (Train, 2002). The index ranges from 0 to 1; the value of 0 indicates that the estimated model has no predictive power, whereas a value of 1 indicates that the model can predict all consumer decisions perfectly. In this study, this index had a value between 0.16 and 0.20; which is within the same range as the log likelihood ratio index values reported in other similar qualitative transportation models (Horne, 2003; Ewing & Sarigollu, 2000).

The perceived additional benefits or costs associated with conventional gasoline vehicles over HEVs due to the attributes not accounted for in the choice experiments are captured in the alternative specific constant. Table 5 above indicates that the ASC is statistically significant across all market conditions. Thus, there are important attributes that consumers considered in their decisions but were omitted from this experiment. However, the influence of these omitted attributes on the models are low, because the alternative specific constants’ contributions to the total utilities are only 3% to 10% (Figure 13).

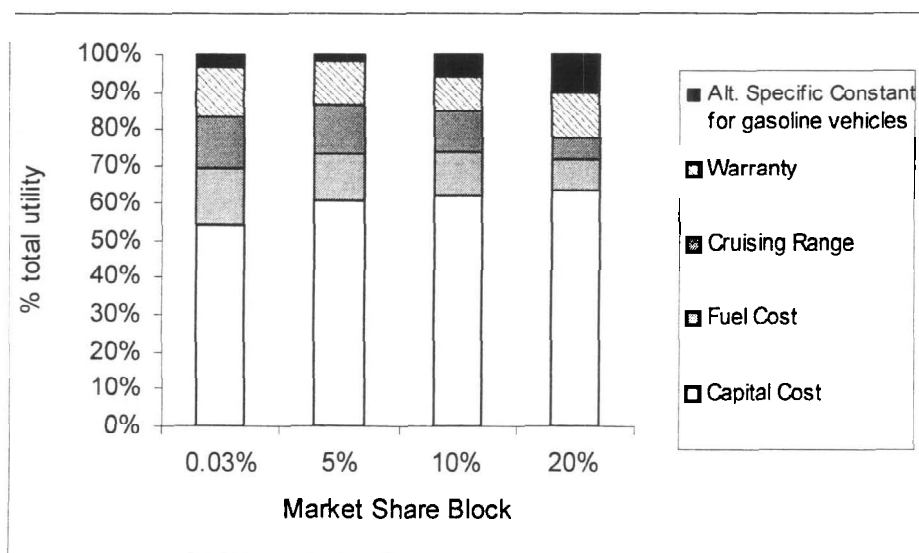


Figure 13 - Utility contribution of attributes from a conventional gasoline Honda Civic

This means that the choice experiment and, subsequently, the derived discrete choice models captured most of the important attributes in consumers' vehicle purchasing decisions. In other transportation studies that are similar to this one, the ASC has also been found to be significant. However, the ASC's contribution to the model is much higher in magnitude, ranging anywhere from 30% to 70% of the total utility, rendering the model outputs in the other studies to be highly determined by the untested attributes captured by the ASC rather than the attributes under study in their research (Horne, 2003; Ewing & Sarigollu, 2000; Eyzaguirre, 2004).

Converting the non-monetary attributes into monetary units (monetization), and then comparing them to their current market values offers an effective way of assessing whether the values consumers place on the attributes are realistic. The monetized cruising range attributes for each qualitative model suggest that an extra day of cruising was perceived to be equivalent to \$150 to \$400. Using the Honda Civic conventional gasoline vehicle, which has a fuel tank of 50L, as an example, an extra day of cruising on the same amount of gasoline saves at least 4.5L of gas every 11 days, which translates to a savings of about \$134 per year. Given that the average lifetime of vehicles is 10 to 16 years, the increase in fuel efficiency would save the consumer more than \$400 dollars over the vehicle's lifetime. This result indicates that the cruising range attribute might be slightly under valued under a discount rate of 21.84%¹, a discount rate which was estimated from this research in the preceding sections.

Monetization of the warranty attribute indicates that an extra year in warranty is worth the equivalent of \$500 to \$850. Unlike the monetized cruising range attribute, the estimate of the warranty attribute was very similar to the extended warranty negotiated

¹ A discount rate of 21.84% would yield a NPV of \$587. Conversely, a discount rate of 30% would yield a NPV of about \$400.

at the car dealerships, which has a market price of \$600 to \$1000 per year (Honda, 2004).

Further exploration of the coefficients indicates that on a dollar-per-dollar basis, consumers perceived subsidies to be about 1.5 to 1.8 times more influential in affecting consumer decisions than capital cost. Thus, a \$1000 subsidy would offset the loss in utility caused by a \$1500 increase in capital cost of the vehicle. This response indicated that consumers valued subsidies (a gain) more than capital cost (a loss), which is a response consistent with the complementary study done by Eyzaguirre (in progress).

The validity of the models is confirmed by the analyses above. The next sections analyze each of the model parameters to draw inferences about consumer values in each of the attributes presented in the choice experiments.

3.3.1.2 Qualitative model parameters

The first question that must be answered before making comparisons among market share blocks is whether consumers place different values on different attributes of vehicles, and if they do, the order of importance must be determined. This question has been investigated in previous research (Honre, 2003; Ewing & Sarigollu, 2000). Nonetheless, it was important to understand the values consumers placed on different attributes specific to this research so that I could effectively explore how consumers' preferences change under different market conditions.

The relative values consumers place on each attribute can be inferred from the utility functions of each qualitative model; in which the utility functions were developed from the results on Table 5. The coefficients of each attribute in the utility functions can be compared to each other in order to assess the values consumers perceive for a one unit increase of each attribute. However, this information is of limited use because the

attributes are different from each other physically. For example, knowing that consumers place higher importance on a one year increase in warranty than a one dollar increase in fuel cost is not very useful.

To assess whether consumers placed different values on different attributes of vehicles, I applied real world attribute values to the utility functions taken from two example vehicles, which resulted in tangible utility numbers for each attribute. Comparing these resulting utility numbers can provide the relative values consumers place on the attributes of a specific vehicle, which is more informative than the coefficients comparison.

In this research, the conventional gasoline vehicle example was the gasoline 2004 model Honda Civic, and the HEV example was the 2004 model Honda Civic Hybrid. Their attributes are listed in Table 6.

	Honda Civic Conventional Gasoline	Honda Civic Gas-Electric Hybrid
Capital Cost (\$)	17100	29510
Fuel Cost (\$/week)	23	13.31
Subsidy (\$)	0	1000
Cruising Range (days / tank)	11	19
Warranty (years)	5	5
Alt. Specific Constant for gasoline vehicles	1	

Table 6 - 2004 Honda Civic Attributes (Honda 2004)

The Honda Civic is a compact to mid-size vehicle, and most (about 65%) of survey participants' vehicles belonged to this class. This vehicle's class, make, and model is popular among Canadians (Autonews, 2003). Thus, it can represent a "typical" vehicle, leading to generalizations about the results. When I weighed the utility values pertaining to the Honda Civic, it was evident that consumers valued the importance of each of the five attributes differently within each model, as presented in Figure 13 and

Figure 14. The data show that capital cost was a relatively large component of total utility in both the conventional gasoline and Hybrid Gas-Electric vehicles, dominating greater than 50% of total utility under all market conditions. This suggests that consumers placed very high importance in capital cost in their decisions. The non-monetary attributes, cruising range and warranty, together comprise up to 20% of the total utility. This indicates that cruising range and warranty coverage were also somewhat important in consumers' decisions, but were not the consumers' main concern in deciding between vehicles.

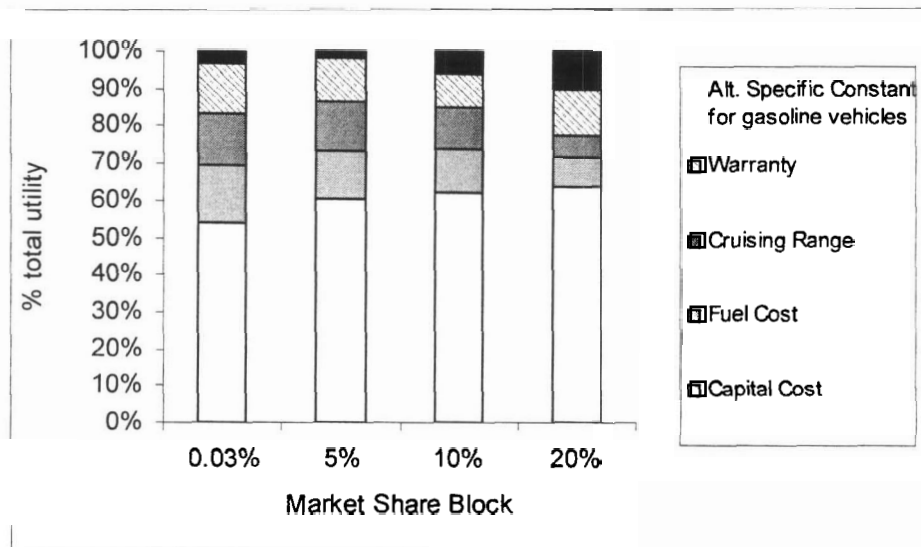


Figure 13 (repeated) - Utility contribution of attributes from a conventional gasoline Honda Civic

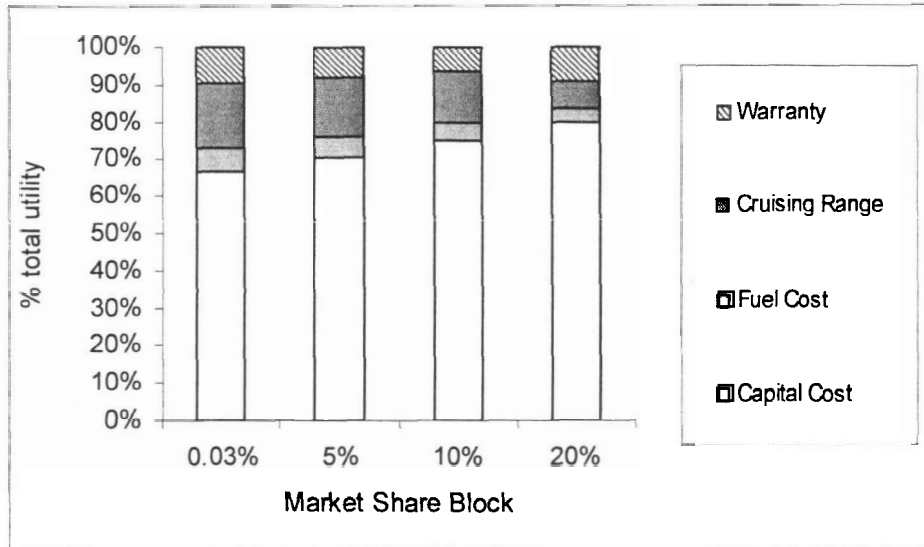


Figure 14 - Utility contribution of attributes from a Hybrid Honda Civic

The results presented above indicate that in choosing between a conventional gasoline vehicle and a HEV, consumers do not value all attributes the same way. To obtain more information about consumer behaviour, I used a process called a “linear analysis” to investigate how consumers valued the importance of changes in vehicle attributes.

The utility functions in the qualitative models assume that the values consumers place on each additional increase of each attribute is “linear”, namely, the utility increase due to a one unit addition to an attribute will always be identical. For example, looking at Table 5, a one day increase in cruising range will always bring an additional 0.0791 unit of utility under market condition 0.03%. However, that may not always be the case. It is possible that the additional utility due to a one unit increase in attributes may change depending on the amount of attributes already present. For instance, the additional utility of a one day increase in cruising range for a very fuel efficient vehicle that only requires a fill-up once a month may be lower than that of a very fuel inefficient vehicle

which requires a fill-up once a week. Understanding these non-linear relationships can provide valuable information to policy makers in designing cost effective policies.

To investigate the linearity of the attributes, I adapted the utility functions to characterize the attributes as discrete categorical variables, rather than as continuous variables. I used the statistical package Limdep 9.0 to obtain new coefficients corresponding to these categorical variables, and expressed the results as “indexes of utility”. The results indicated that consistently throughout all market shares, non-linear relationships exist for subsidy and cruising range, whereas the remaining attributes have linear relationships. The nature of the nonlinear relationship for subsidy and cruising range is very different. Figure 15 below is an example of the subsidy attribute, with the bars indicating the 95% confidence interval. The index of utility shows that consumers find little additional value of higher increases in subsidy for hybrid vehicles if the total subsidy amount is between 5% and 10% of the vehicle price. However, once the subsidy offered is higher than 10% of the vehicle price, then any additional increases become much more important in the consumers' decision in choosing the HEV. This indicates that higher subsidies are more appealing to the consumer than lower subsidies.

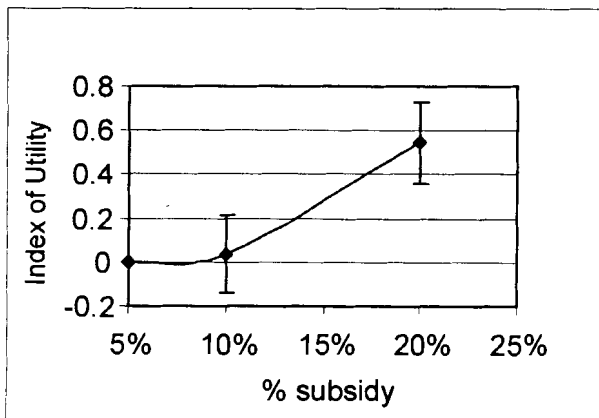


Figure 15 - Example of a non linear relationship for subsidy attribute

For the linearity relationship in cruising range, consumers seem to value cruising range improvements for HEVs if the cruising range is 0% to 50% higher than a comparative conventional gasoline vehicle. However, consumers attributed less importance to a higher cruising range in the HEV when it achieves a 50% or better cruising range than conventional gasoline vehicles. This indicates there is diminishing additional consumer value in improving the HEV's cruising range once it is 50% better than conventional gasoline vehicles (Figure 16).

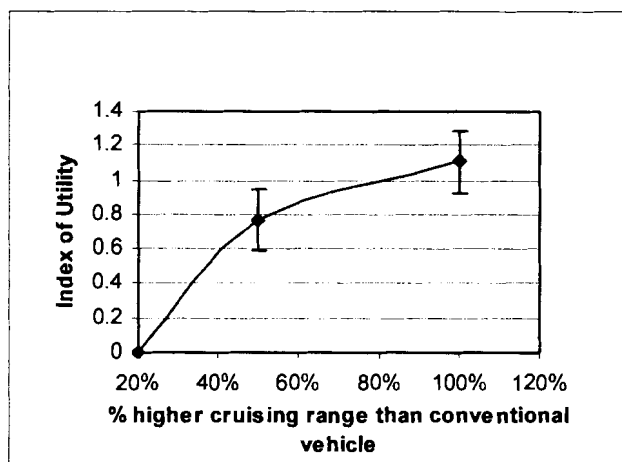


Figure 16 - Example of a non linear relationship for cruising range attribute

Overall, the results from the model estimates indicate that consumers placed different importance on each of the five attributes tested in the discrete choice models. This is consistent with results from past studies (Horne, 2003; Ewing & Sarigollu, 2000); however, consumers valued some attributes differently as the attribute values changed, reflecting a novel result. The results presented thus far set up the foundation that is required to compare how consumer values and behaviours change with market conditions, the primary objective of this research.

3.3.2 Comparisons among market share blocks

Addressing whether consumers' values change in response to market share conditions of HEVs requires comparing the results from the discrete choice models of each market share block. Since "utility" is an arbitrary value that describes the importance of attributes relative to each other within a utility function, comparing the attribute coefficients between the four utility functions will not yield meaningful results. Thus, to compare the different values consumer place in each of the five attributes between market share conditions, they first need to be standardized, that is, brought to a common base. In this case, I have chosen to standardize them as a function of changes in capital cost, so that all comparisons can be in dollar amounts. As a result of making these comparisons, I have found trends in consumers' preferences with increasing HEV market share; these trends are evidence that consumer values change with different market conditions. Three of the most pronounced trends are presented below.

The first observed trend is associated with the ASC. The ASC captures the perceived benefits or costs associated with gasoline vehicles over HEVs due to attributes not considered in this research, given that the five attributes that were observed in the model are of equal value (i.e., *ceteris paribus*). It was found that, with an increasing HEV market share, the standardized value of the ASC declined with increasing HEV market share (Figure 17). This trend suggests that consumers view conventional gasoline vehicles as becoming less desirable with increases in HEV adoption, *ceteris paribus*. Previous literature indicated consumers are concerned about the performance, reliability, and safety of HEVs (Horne, 2003; Ewing & Sarigollu, 2000); however, these attributes were not examined in this research so it is unknown whether these attributes caused the reported trend. With increasing HEV market share, these concerns may subside, or other concerns, such as environmental friendliness, may

become important to consumers. Although the “environmental friendliness” factor is not part of this research, this survey included a question to assess whether consumers would be willing to spend more money to buy an ecologically friendly technology. The percentage of respondents who stated they would be willing to buy an ecologically friendly technology increased from 59% to 67% from low to high HEV market share blocks. Thus, it is recommended that this speculation should be tested in future research.

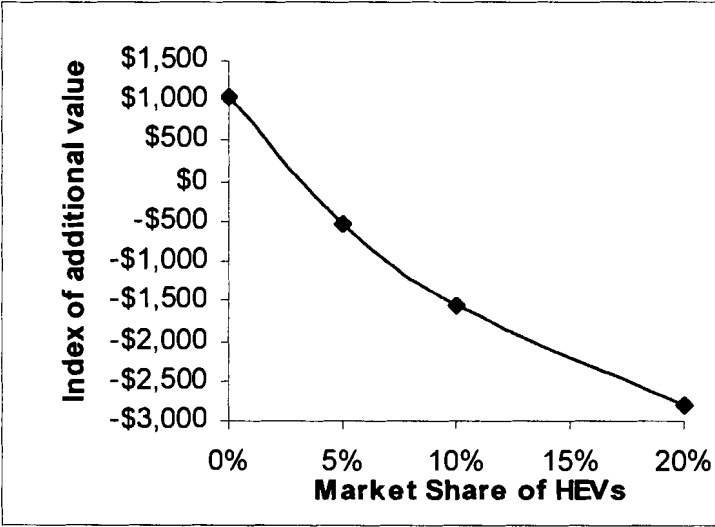


Figure 17 - Valuation of the ASC for gasoline vehicle

The second trend that I observed is that the perceived undesirability of higher fuel prices declines with increasing market share of HEVs (Figure 18). This trend suggests that with a higher market share of HEVs, consumers are likely to view fuel cost as a less important consideration in their vehicle choice. I speculate that this trend is due to the effect of averages. If more people adopt HEVs under higher HEV market shares, then it is likely that on average the population will be less concerned about fuel costs because HEVs are fuel efficient. An examination of the choices the survey participants made concludes that the percentage of HEV choices ranged from 49% to

56% with an increasing market share of HEVs. This difference may explain at least part of this trend for fuel cost.

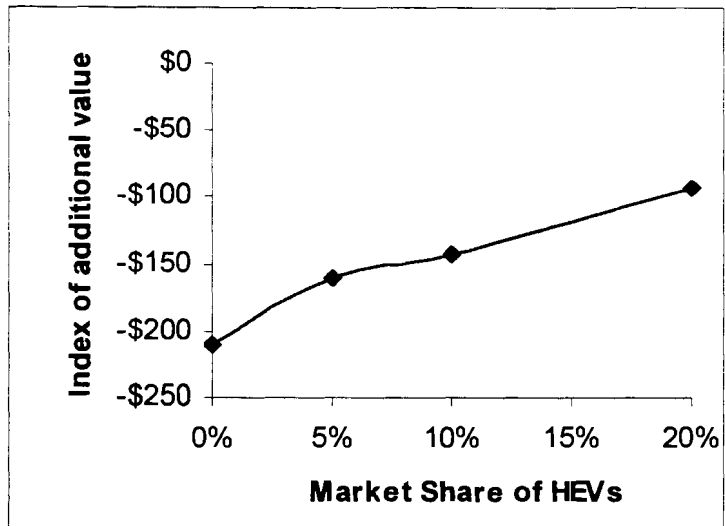


Figure 18 - Valuation of \$1 increase in monthly fuel cost as capital cost

Finally, the perceived benefit of longer cruising range declined with a higher HEV market share (Figure 19). This indicates that consumers perceived higher cruising range as more important in their vehicle decisions when there are less HEVs on the road as opposed to more HEVs on the road. The relationship is linear. For example, for every five percent increase in HEV market share, there is an \$80 reduction in perceived benefits. There is no clear explanation as to why such a trend may exist. I speculate that the information provided in the IA portion of the survey for the four market share treatment groups might have presented continuously lower emphasis on the value of cruising range in relation to other vehicle attributes, causing its importance to steadily decline.

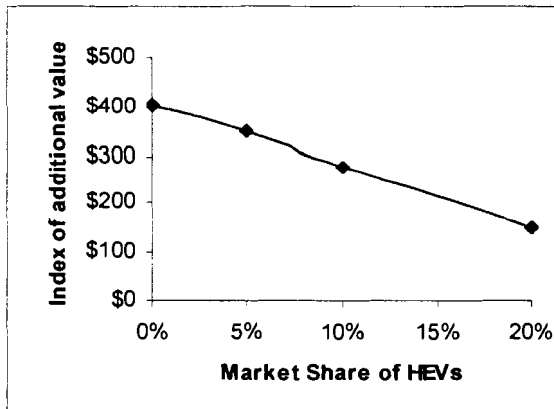


Figure 19 - Valuation of a 1 day increase in cruising range as capital cost

Further investigation into the total effects reveals two additional observations as market share of HEVs increase (ie. the “neighbour effect” becomes stronger): (1) the importance consumers placed on the non-monetary attributes generally decline; (2) the net consumer value of non-monetary attributes for the HEV was always higher than that of the conventional gasoline vehicle. The combined effect of these two observations indicate the net value consumers found in the non-monetary attributes of HEVs over the ones in conventional gasoline vehicles increased with a higher HEV market share. That is, given that the monetary costs of conventional gasoline vehicles and the HEV are identical, consumers’ preference for HEVs become stronger as more people drive HEVs. Figure 20 presents this trend, with the “Consumer value index” representing utility in \$’s.

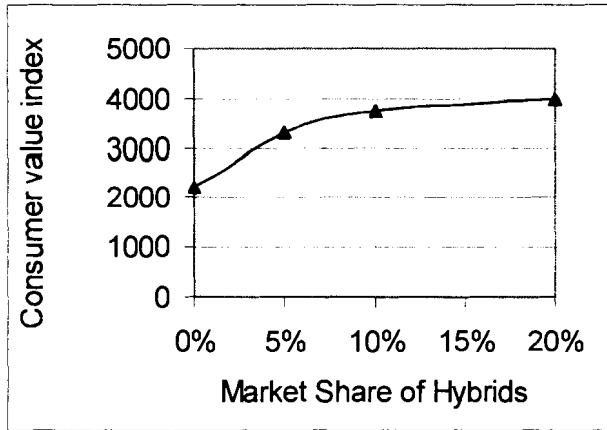


Figure 20 - Net difference in the effects of non-monetary attributes for Honda Civic Hybrid over the conventional Honda Civic in \$ equivalents of utility as “the “consumer value index”.

Using the input values of the example vehicles, Figure 21 presents the probability of consumers choosing HEVs over conventional gasoline vehicles if the two vehicles incur the same financial costs (capital cost and fuel cost). The probability of consumers choosing the HEV is always greater than 50% under all market conditions, thus, given only the differences in the non-monetary attributes between HEVs and the conventional vehicle, consumers will always be more inclined to choose HEVs. If the relationship between the probability of choosing HEVs and the market share of HEVs is linear, as estimated by the solid black line in figure 21, then the probability of consumers choosing HEVs would generally increase with higher HEV market share. Note that, however, at market share 10%, the probability of consumers choosing HEVs is abnormally high. This point, like others, is a result of the most likely estimate from the data. I speculate that the range of uncertainty around this point estimate will likely encompass the linear trend estimated.

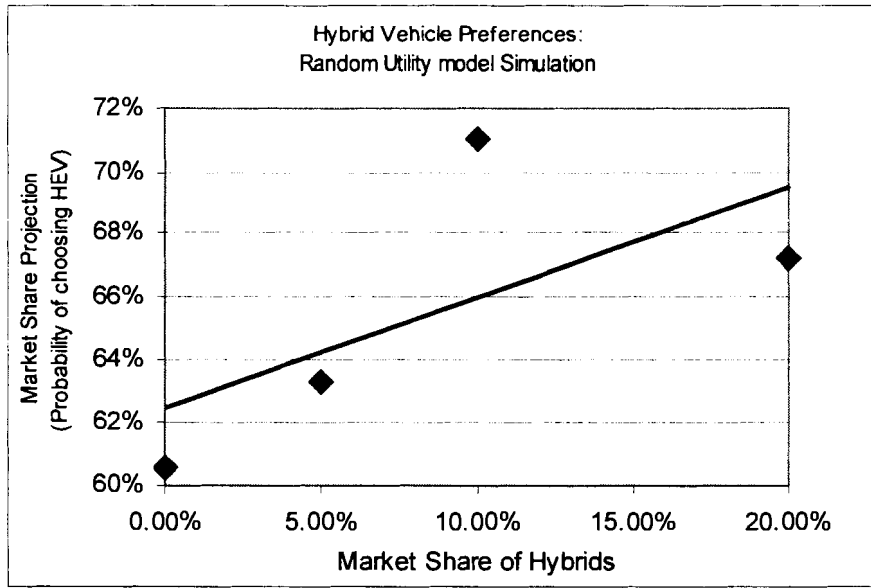


Figure 21 - Combined outputs of the four discrete choice models, given that the financial costs of HEV and conventional gasoline vehicles are identical

However, after I adjusted the financial costs of both vehicles to reflect the actual market price, the desirability of HEVs decreases dramatically due to the high importance consumers placed on financial costs. In particular, the higher capital cost of HEVs, which is about 1.5 times the price of a conventional gasoline vehicle, dwarfs the gains in desirability of the non-monetary attributes. Figure 22 contain forecasts from the discrete choice models given that the price difference between conventional gasoline vehicle and HEVs will always remain the same. It indicates that HEVs do not gain much more than 20% in market share. The differing effects in consumer behaviour among the four market share blocks are suppressed by the large difference in capital cost.

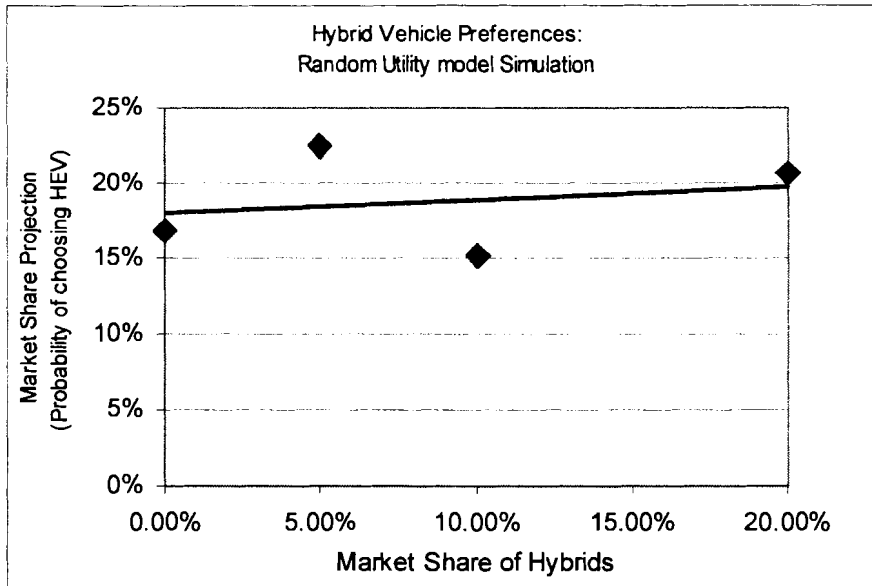


Figure 22 - Combined outputs of the four discrete choice models with actual attributes of the Honda Civic Hybrid and the Honda Civic conventional gasoline models

Combining the actual financial and non-monetary attributes of the Honda civics with (1) the effect of a learning curve with a progress ratio of 0.75, and (2) the effect of changing market shares of HEVs (ie. the "neighbour effect") results in a trend as illustrated in Figure 23 below. The combined effect is linear and positive, with the probability of consumers choosing HEVs increase with HEV market share. The learning effect substantially improved the consumer response on HEVs over conventional gasoline vehicles, since lowering capital costs of HEVs to match that of conventional gasoline vehicles will raise the importance of the positive non-monetary attributes from the HEV. Note that the stocks of HEVs used to estimate the learning curve effect for this figure is obtained from the reference CIMS simulation outputs, which will be discussed in the next chapter.

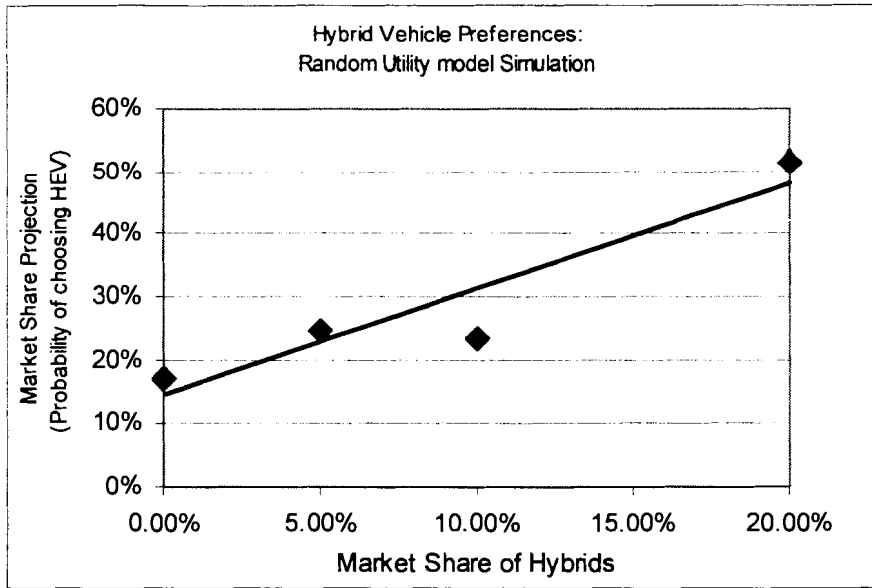


Figure 23- Combined outputs of the four discrete choice models with actual attributes of the Honda Civic Hybrid and the Honda Civic conventional gasoline models, plus the addition of the learning curve at a progress ratio of 0.75

Comparing the results from the attributes across the four market share conditions indicates that consumers valued attributes for conventional and hybrid vehicles differently in response to changing market share conditions. Quantifying how consumer values change reveals that the differing values occurred in non-monetary attributes; however, the effects of these consumer values on consumer decisions were overshadowed by the large capital cost difference between the conventional vehicle and the HEV. Nonetheless, the changing consumer values towards non-monetary attributes are important to characterize and translated into CIMS because they will play an increasingly important role in consumer decisions when the cost of HEVs decline overtime through processes such as learning, namely, manufacturers becoming more efficient at producing HEVs as more are produced.

3.4 Translating discrete choice model outputs to CIMS

Recent changes to CIMS give it the ability to simulate technological change with internal functions that (1) relate the financial costs of technologies to cumulative production and (2) adjust the intangible costs of adopting a new technology as market shares change. Previously, the capital costs of technologies were determined outside the model, and were input as constants. Consumer preferences were informed by three main parameters: r , the discount rate; i , the intangible cost factor; and v , the market heterogeneity parameter. The three main parameters for consumer preferences for most technologies were estimated from expert opinion and past market data, and were also input as constants. They were not “internalized” and “dynamic”, that is, self-adjusting due to changing conditions during model simulations.

To improve the realism in consumer preferences, past researchers working with CIMS have tried to use consumer preference surveys as a means to acquire more realistic parameters, and so far, this has been done for select technologies related to vehicle types, commuting modes, residential renovations, home heating systems, and industrial steam generation systems. While these newer parameter estimates may be more reflective of the real world, the parameters are static and thus not indicative of changes that may occur as market conditions evolve.

In my research, I transformed the information from the discrete choice model in order to estimate the behavioural parameters that are specific to HEVs in CIMS. More specifically, I used the outputs of the discrete choice models to inform the “intangible cost function” in CIMS, which internalizes the i parameter and makes i dynamic by linking the value of non-monetary attributes of a technology in a given simulation period with the market share of that technology in the previous simulation period. Thus, the result of CIMS modelling exercises will reflect the changes in consumer behaviour

toward non-monetary attributes of technologies as market conditions change, namely, reflecting “dynamic consumer behaviours”.

Additionally, I activated the declining capital cost function in CIMS in my modelling exercises in order to internalize the capital cost parameters for HEVs and make them dynamic. This function simulated lowered costs due to learning as more of the same technology is produced over the simulation periods. Modelling these two dynamics, the intangible costs and the capital costs of HEVs, in the CIMS model represents two major innovations in portraying consumer behaviour over similar past studies for CIMS with respect to simulating long run policies. The declining capital cost function allows the capital costs of new technologies to fall to the point where they may become more competitive with incumbent technologies, triggering a potential for wide consumer adoption. Once this potential is reached, the major factors determining consumer adoption will be these “intangible” non-monetary attributes, which are represented by the declining intangible cost function.

To implement these innovations in CIMS, I converted the discrete choice modelling results of the example vehicles - the 2004 model conventional gasoline Honda Civic and Honda Civic Hybrid, into parameters in CIMS. In the sections below I will describe how I estimated the discount rate, intangible cost function, and the market heterogeneity parameter from the discrete choice models in this research, and how I obtained the declining capital cost function for HEV externally.

3.4.1 Discount rate

Translating the discount rate estimated from the qualitative model to CIMS' r parameter can be done by valuating the capital cost in terms of annual fuel cost over the lifespan of the hybrid technology (Horne, 2003). Equation 11 describes how this process

takes place, where β_{CC} is the beta coefficient of capital cost estimated in each qualitative model, β_{FC} is the beta coefficient of fuel cost in each qualitative model, and “n” is the predicted lifespan of the HEV. These beta coefficients are taken directly from the parameters of the utility functions for each market share block. Using this method, I estimated a distribution of private discount rates for hybrid vehicles for each HEV market share scenario, assuming that HEVs have a technological lifespan of 16 years, similar to conventional vehicles (Figure 24). The results show that the private discount rate is dynamic, namely, it increases with higher market shares of hybrids. This shows that as more HEVs are present on the road, consumers become less concerned about the ongoing costs of HEV's, but relatively more concerned about the immediate purchasing costs. Unfortunately, I cannot directly translate the dynamic nature of the private discount rate into the CIMS model because r is a fixed constant in CIMS. However, I can illustrate the range by running example simulations using different discount rates. For the majority of my simulations and my work in CIMS I chose the discount rate of 21.84%, which reflects the current market condition of hybrid vehicles (0.03% market share), and the expected lifespan of hybrid vehicles (16 years). This value indicates that consumers place little importance on costs incurred with the vehicle in the future, which is consistent with the findings in similar transportation studies (Honre, 2003; Ewing & Sarigollu, 2000).

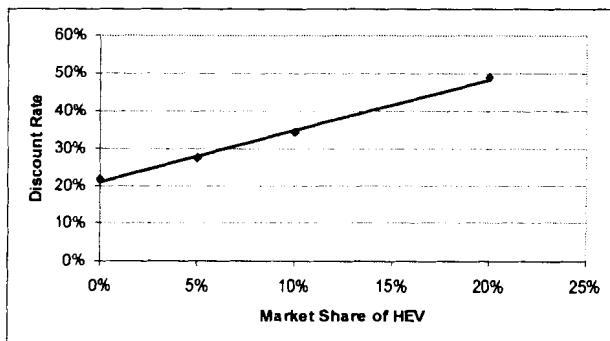


Figure 24 - Discount rate estimates from the four qualitative models for a typical HEV

3.4.2 Dynamic (declining) intangible costs

Prior to this research, intangible costs for technologies in CIMS were entered as constants (CIMS, 2004). However, results from this research will make use of the intangible cost function that calculates intangible costs at any time period as a function of new stock market share.

Using the method outlined in 2.3.1, the non-monetary attributes in the discrete choice models under each market share condition are translated into the declining intangible cost function in CIMS. Table 7 outlines the parameters estimated for this function using the Honda Civic Hybrid example. The intangible cost function is illustrated graphically in Figure 25.

CIMS parameters		
lo	A	K
4349.321	0.362867	6.981808664

Table 7 - Estimated Intangible cost function parameters from example HEV

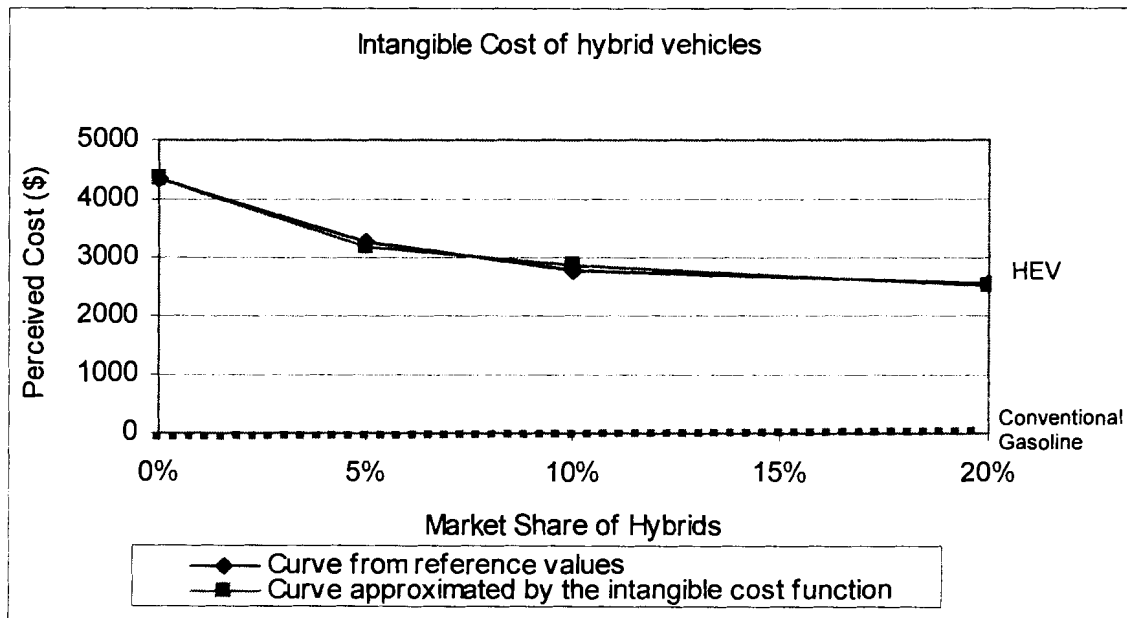


Figure 25- Intangible cost function of an example HEV. Costs shown are relative to that of the conventional gasoline vehicle

The solid curve in Figure 25 denoted by squares is plotted from the combination of the four discrete choice functions from each market share block; the solid curve denoted by the diamonds is approximated by the intangible cost function approximated using the parameters in Table 7. The curves are almost identical to each other, indicating a very good fit. The “intangible cost function” defines consumer values as a “cost” on the y axis, with higher costs representing less desirability by consumers. Since intangible costs are not true monetary costs, they must be treated as relative costs between competing technologies in model simulations. Historically CIMS researchers have calibrated the intangible cost of electric vehicles as the zero baseline, and conventional gasoline vehicles’ intangible costs were set at \$6555 more than the electric vehicle, reflecting consumer attitudes between these two technologies. For the purpose of this study, I chose to deviate from this convention and discuss the HEV’s intangible cost (solid lines) relative to that of the conventional gasoline vehicle (dotted line). The HEV’s intangible cost curve in Figure 25 is declining, indicating that consumers find the non-monetary attributes of HEVs more desirable relative to those of the conventional gasoline vehicle as the HEV market share increases. This result in the CIMS intangible cost function is consistent with that of the discrete choice model as depicted in Figure 20, indicating a successful translation of the non-monetary parameters in the discrete choice models to the intangible parameters in CIMS. This result implies that, in the long run, when the capital cost of HEVs have declined to match the cost of conventional gasoline vehicles, the intangible costs from non-monetary attributes will play a significant role in consumers’ decisions on vehicle choice. In addition, the result suggests that, in the long run, as the market share of HEVs improves, consumers may favour HEVs over conventional gasoline vehicles when other attributes are equal.

3.4.3 The variance parameter

The variance parameter, “ v ”, represents market heterogeneity in CIMS. A higher value of v indicates higher cost responsiveness and less market heterogeneity (Horne, 2003). With an extremely high value of v , consumers and businesses would behave like a linear programming model in that all would choose the same technology, even if it were only slightly cheaper in a single point estimate.

The variance parameter, v , was estimated according to the method outlined in section 2.3.3. Like the private discount rate, the variance parameter is static in CIMS. Thus, I chose to estimate this parameter using the qualitative model from the HEV market condition of 0.03%, which reflects the situation as it exists today. The estimated v parameter was 2.40, which is consistent with v parameters estimated from past research on new technologies (Horne, 2003; Rivers 2003).

3.4.4 The declining capital cost function

The declining capital cost function (Equation 7) is the internal driver in CIMS that incorporates into its simulations the lowering capital cost of new technologies due to learning. As outlined in section 2.2, the main parameter in this function is the progress ratio (PR), which must be estimated from engineering-economic models or from revealed market information. Thus, estimating this parameter is beyond the scope of this research. However, based on the projection by Lipman and Delucchi (2003) that HEVs will cost about \$2000 more than conventional gasoline vehicles in year 2035, I estimated that a progress ratio of 0.75 was adequate to achieve these external capital cost forecasts. A progress ratio of 0.75 indicates that, with each doubling of cumulative production, capital costs decline by 25%. I used this value in my policy simulation exercises.

3.4.5 New CIMS verses old CIMS

To illustrate the differences in modelling results from the new version of CIMS, which contained the innovations developed in this research (new CIMS) and the previous version of CIMS (old CIMS), I compared simulation results from both versions, using the characteristics from the Honda Civic conventional gasoline vehicle and the Honda Civic Hybrid as input values. To make the comparison fair, both versions of CIMS have the same competition node structure, for which a simplified version is illustrated in Figure 26 below. I applied the same “Business as Usual” condition to each version of CIMS, which represent the current economic conditions in Canada with no policy adjustments - a condition that all CIMS researchers use as their baseline condition. I also analyzed the simulation results coming from the same competition node (shaded box). The only differences between the two versions are the aforementioned parameter values which I have updated from my study.

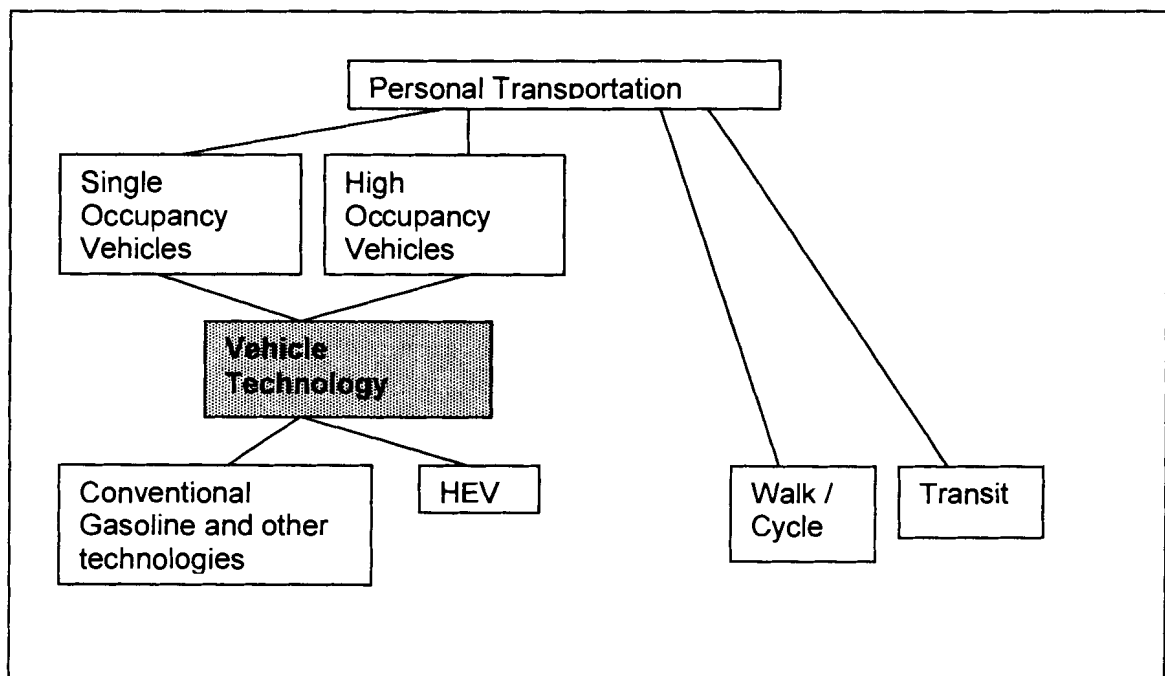


Figure 26 - Competition node structure for old CIMS vs. new CIMS simulation

The differences in the results from the two versions of CIMS are substantial. The results suggest that the old CIMS may have underestimated the dynamics in markets. Incorporating these dynamics as in the case of the new CIMS may lead to very different simulation outcomes. Figure 27 illustrates that the new CIMS projected HEV adoption is much higher than the old CIMS.

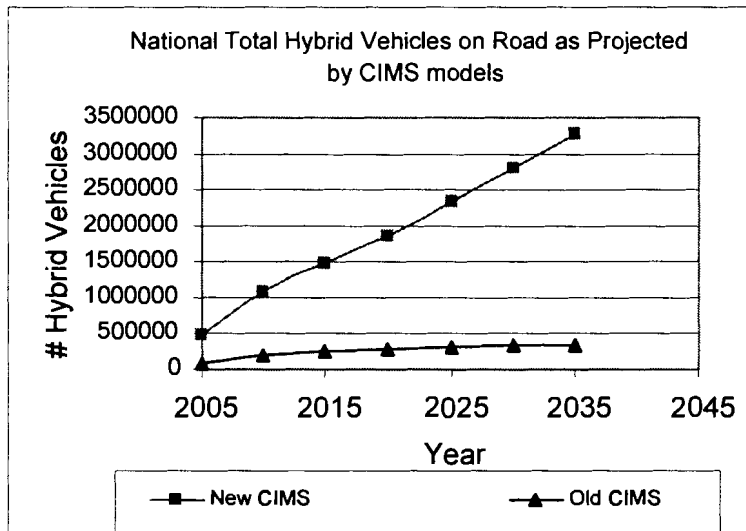


Figure 27 - CIMS Simulation, total HEVs

Figure 28 illustrates that the new CIMS projected a more optimistic market share of HEVs than the old CIMS. Specifically, new CIMS indicates HEVs gain higher market shares of passenger vehicles over time, for both the market share of new HEV stocks and the total HEV stocks on the road each year, whereas the results of the old CIMS indicate the HEV adoption to remain low and stagnant.

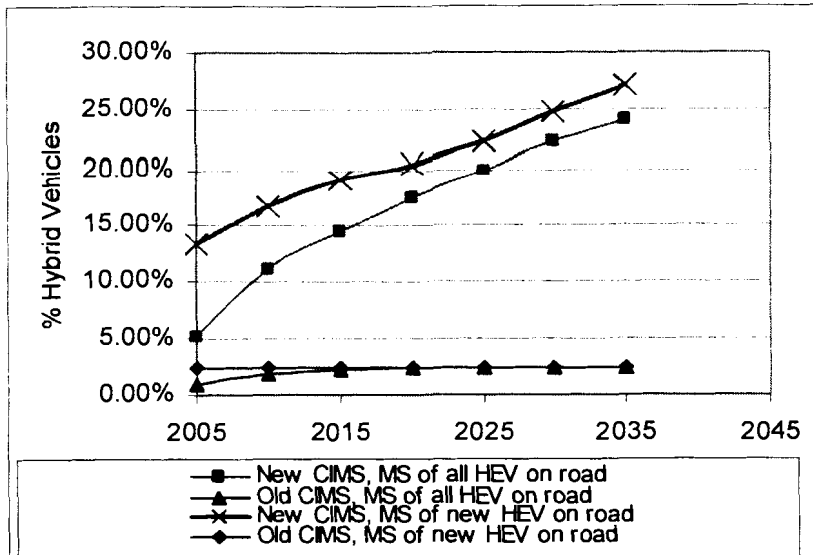


Figure 28 - CIMS Simulation, % Market Share of HEVs

Activation of the declining capital cost function in the new CIMS causes the capital cost of HEVs to decline at a progress ratio of 0.75. A declining capital cost of HEVs relative to conventional gasoline vehicles will likely attract a higher adoption of HEVs. However, the increase in national total HEVs is also explained by the declining intangible cost function in CIMS. This is shown in Figure 29, which illustrates the number forecast of new HEVs purchased through time in Ontario; the trend from Ontario is representative of the trend across all provinces².

² The simulation from Ontario is representative of all provinces because the input variables are identical across all provinces

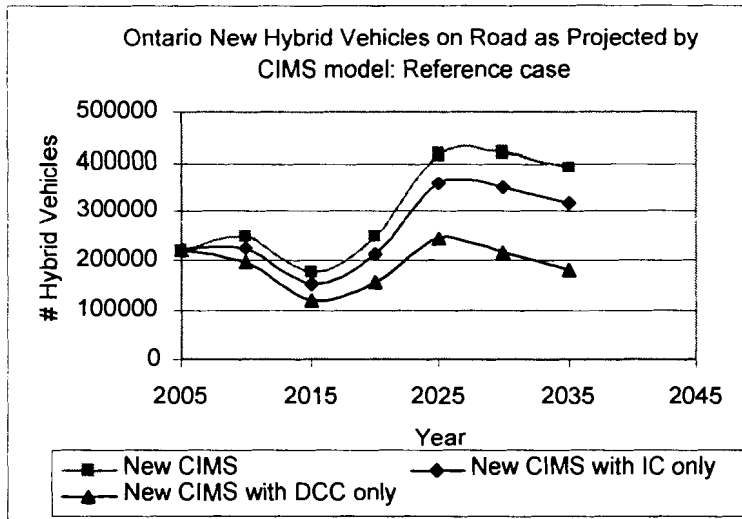


Figure 29 - CIMS Simulation, New HEVs for Ontario

The line denoted by triangles illustrates the effect on new purchases attributable to declining capital costs. The line denoted by diamonds illustrates the effect on new purchases attributable to the declining intangible cost function. The line denoted by the squares illustrates the total effect of both functions. Note that the intangible cost function's contribution to new vehicle purchases increases with time due to changing consumer preferences as different market shares of HEVs were experienced in the model simulation. This result supports the hypothesis that the intangible cost plays a larger role in consumer decisions when capital cost declines.

While the aforementioned trends are clear in figure 29, all curves have an oscillating pattern. It is caused by the retirement function of old vehicles in CIMS, which was defined by previous researchers. It is not the result of the model inputs informed by my research.

3.5 Uncertainty in model parameters

In the previous sections, I have reported results based on the most likely estimates. However, consumer decisions are highly varied and so there is value to decision makers in understanding the plausibility of these estimates in the outputs of the discrete choice models and in the CIMS model. This “plausibility” indicator can be characterized by exploring alternative discrete choice model parameters and their relative merits, and by exploring the resulting CIMS model outputs.

3.5.1 Uncertainty in the discrete choice models

I performed a Bayesian uncertainty analysis on the parameters of each of the four discrete choice models. With this approach, I calculated the probability of other possible values for the parameters’ coefficients that can replace the most likely estimate (MLE) coefficients as reported in Table 5. The information from the probability distributions of these possible values can be categorized into two general types. The first type is “diffuse”, as illustrated in Figure 30. A diffuse Bayesian probability distribution for a parameter has a very wide spread, meaning that there is a very large range of probable parameter values, each having about the same probability as the others. In this type of distribution, the probability of the MLE for a parameter might be similar to other possible values. Thus, the degree of belief in the deterministic MLE estimate is low. Analysts observing such diffuse distributions should be aware that other estimates (that are just as probable) exist and these other values must be taken into account in the modelling projections. The second type of Bayesian probability distribution for a parameter is “distinct”, where the probability distribution of the possible values for a parameter takes on a distinctive shape, with a peak indicating that one of the estimates is much more probable than other estimates. The distinct Bayesian probability is illustrated in Figure 31. Parameters with a distinct probability distribution

indicate that the degree of belief in the deterministic MLE is high, enabling analysts to have high confidence in using modelling projections that incorporate only the MLE.

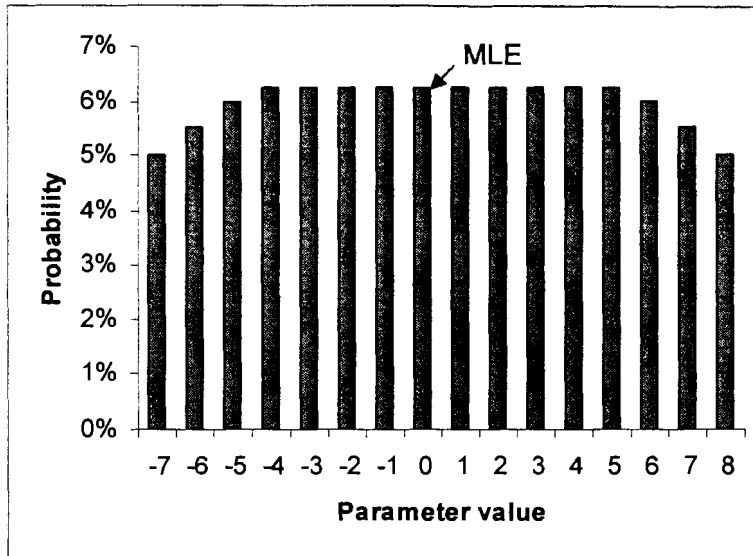


Figure 30 - Example of a diffuse Bayesian distribution for a parameter

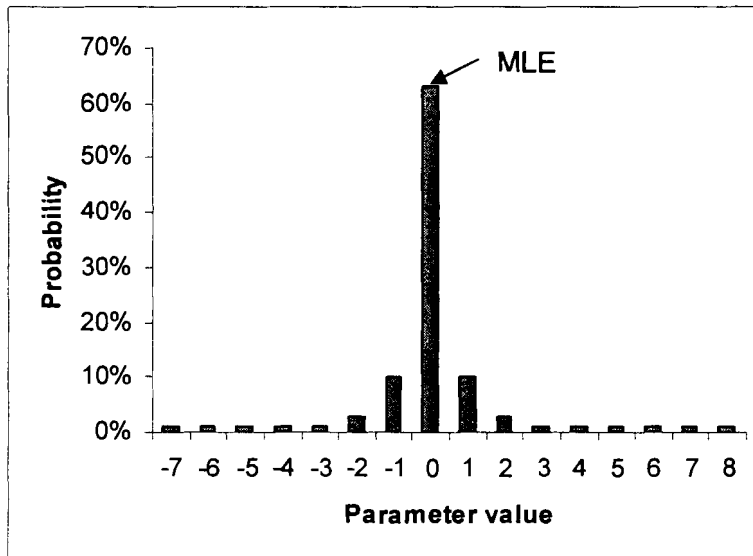


Figure 31 - example of a distinct Bayesian distribution for a parameter

The uncertainty analyses on the parameters of this study indicate that the probability distribution is generally diffuse for all attribute coefficients across all market share blocks. This distribution is presented in Figure 32, which shows the probability distribution of the fuel cost coefficient for HEV market share 0.03%. Note that the

probabilities of the various possible estimates of the coefficient (ranging from -1000% to +1000% of the magnitude of the current estimate) are very similar. Thus, there is a good chance that the coefficient for fuel cost can fall anywhere within this range.

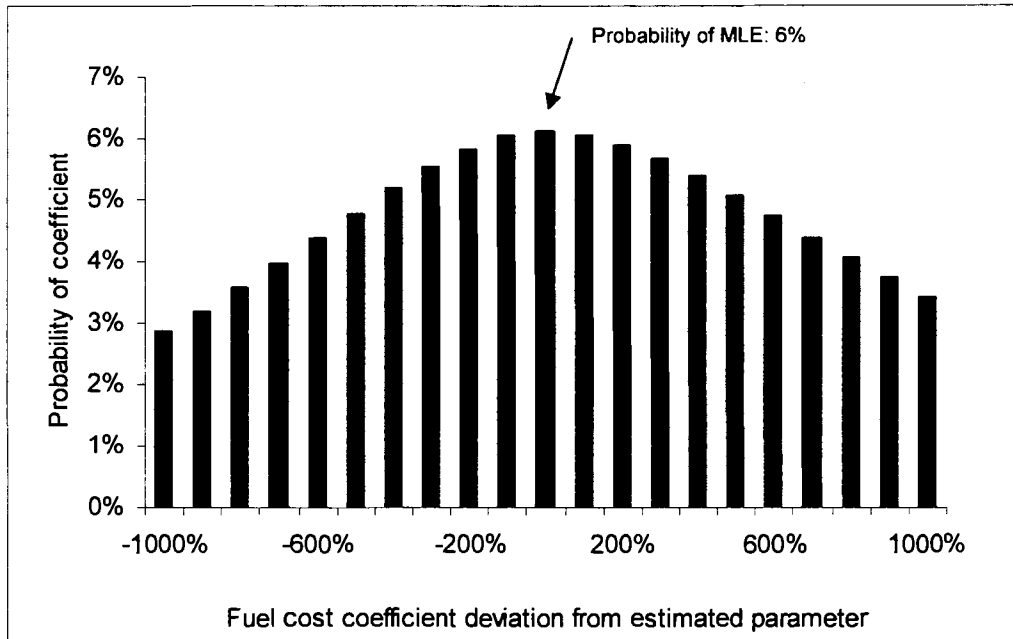


Figure 32 - Bayesian probability distribution of Fuel cost for Market share block 0.03%

Since other parameters have the same diffuse distributions, the degree of belief in the current deterministic MLE estimates is not high. Rather, many other parameter estimates are also likely, and the discrete choice model must take these other values into account in its output projections so that the results are informative and useful for the analysts. Using the attributes from the Honda Civic Hybrid and Honda Civic Conventional vehicle examples, all of the Bayesian probability distributions of all parameters for each HEV market share condition are combined according to the procedure as outlined in the methods section 2.4.1. The method limited the range of possible coefficient estimates for each coefficient is to a deviation that is +/- 20% away

from each coefficient's MLE, for a total deviation of 40%. I chose to limit the uncertainty range rather than using the full uncertainty distribution because I felt that the values captured within the 40% deviation from the MLE will be roughly representative of each parameter's uncertainty distribution, while keeping each parameter in a plausible range. Using the full uncertainty range of each parameter will extend the parameters too far away from the MLE such that the results from this analysis are implausible. For instance, using the full uncertainty range for the capital cost parameter may result in a negative parameter, indicating that consumers perceive higher costs as benefits, which is very unlikely in the real world. Figure 33 below is a probability distribution of possible outputs of the discrete choice model previously illustrated in Figure 22. The peaks of each probability distribution for each market share block represent the MLE output estimated for each market share. The probability distributions of the discrete choice outputs are distinct, with the MLEs gaining the highest probability relative to other possible estimates. This result indicates that while the degree of belief in the MLE coefficients of each attribute from the discrete choice models is low, *the degree of plausibility in the discrete choice model outcomes is satisfactory*. This discrepancy in uncertainty between the parameters and the model outcomes is partly an artefact of the method to estimate these distributions, which carries the major assumption that consumer's stated preferences are most represented within 40% of the MLE coefficient for each attribute. Expanding this range of possible coefficient estimates may slightly expand the probability distribution for the outcome of each market share. However, for the purpose of this research, the very distinctive and "sharp" peaks indicate that most of the total combined effects of all possible coefficient estimates for all attribute coefficients are captured within this range.

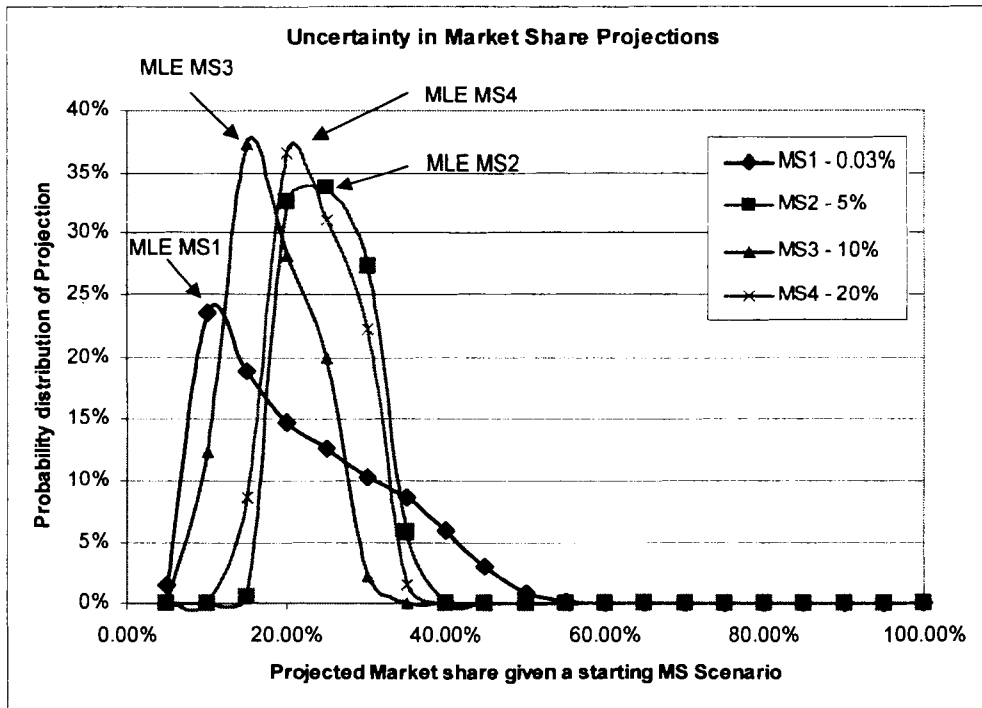


Figure 33 - Probability distribution of discrete choice model outputs

The uncertainties in the discrete choice models must be transferred to CIMS because the discrete choice model outputs and its parameters are used to inform CIMS' intangible cost function. The results of this transfer are described in the next section.

3.5.2 Uncertainties in CIMS simulation results

Uncertainties in CIMS are inherited from the discrete choice model through uncertainties in the discount rate r and the intangible cost function i . Unfortunately, CIMS cannot directly input a range of values for the discount rate and the intangible costs with their respective Bayesian probabilities. Similarly, the CIMS simulation only outputs point estimates. However, the uncertainty can be characterized by highlighting a range of possible values where the CIMS simulation results may fall. By running separate simulations on the limits encompassing the possible discount rates and possible intangible costs of the Honda Civic vehicle examples, the range is created.

As illustrated in Figure 34, the Bayesian probability distributions in the discount rates for all market shares are diffuse with the most probable values falling between a discount rate of about 10% and 30% (within the grey area).

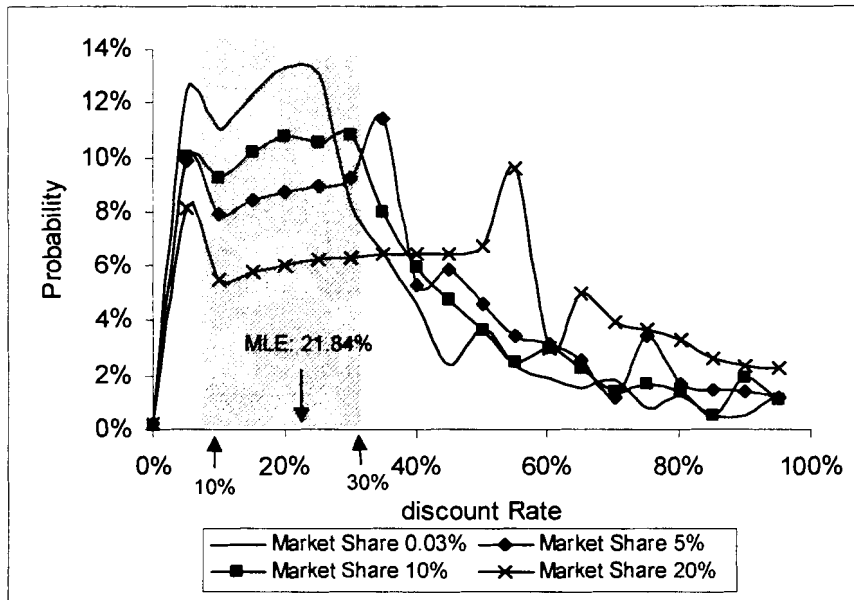


Figure 34 - Probability distribution of discount rate

To transfer this uncertainty to CIMS, a CIMS simulation using the example Honda Civic conventional vehicle and the Honda Civic Hybrid was run, first with r of 10%, then again with the MLE r of 21.84%, then lastly with r of 30%. Analysts should be aware of the combination of these three outputs that highlight the uncertainty range in CIMS (Figure 35). A lower discount rate in the simulation results in a higher projection of new HEV purchases; a lower discount rate implies that consumers are less concerned about upfront costs and view the low ongoing fuel costs of the HEV as more important. The range of values encompassed by the top and bottom curves represents the range of uncertainty in the CIMS simulation due to uncertainty in the discount rate. For example, in year 2015, the high estimate is 600,000 new HEVs, whereas the low estimate is 300,000 HEVs. Analysts should interpret this result as the number of new HEVs

projected by the CIMS simulation being *somewhere* between 300,000 and 600,000 as opposed to reporting only the simulation result from the MLE, which is 400,000 HEVs. The expansion and contraction of the range of possible new HEVs indicate that the uncertainty in new purchases due to HEVs increase quickly from the first year of simulation at year 2005, then declines slightly at 2025, and then increases again toward 2035. The large range of uncertainty in CIMS outputs due to uncertainties in r indicates that the discount rate may require more research in order to reduce the uncertainty and make CIMS' outputs more precise, especially for long run policy simulations.

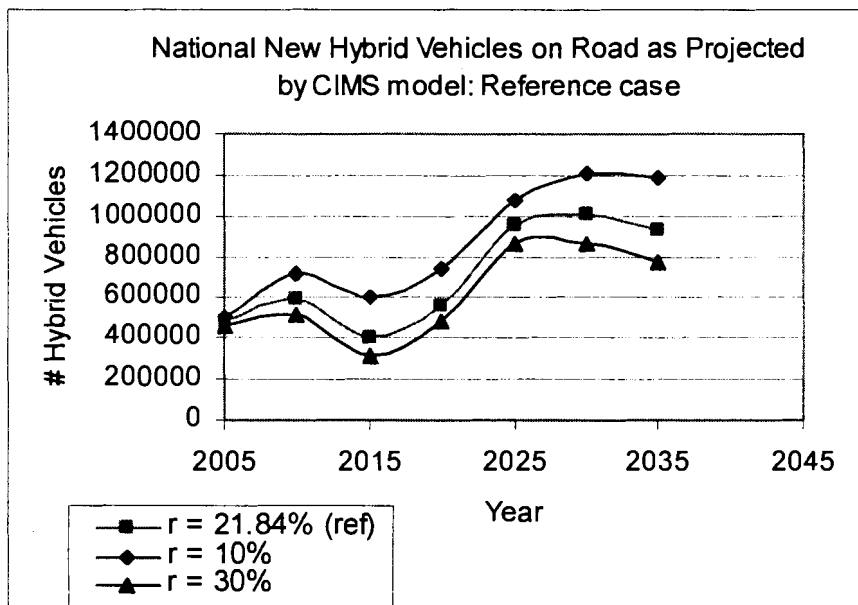


Figure 35 - Sensitivity analysis on r , with CIMS output being national new HEVs

The uncertainty in CIMS due to the uncertainty in the intangible cost function can be characterized in a similar way to discount rates, as described in section 2.4.3. I obtained the high and low limits for the CIMS simulations representing the range of uncertainty due to intangible costs for three separate intangible cost functions. The first intangible cost function is estimated based on the combination of warranty, cruising range, and ASC coefficients that will yield the highest utility, within the limits of their respective Bayesian distributions. The second intangible cost function is estimated

based on the same attributes, but with the combination of coefficients that will yield the lowest utility within the limits of their respective Bayesian distributions. The third intangible cost function is estimated based on the same attributes' MLE coefficients as a reference comparison. For simplicity, I held the capital cost coefficient at its MLE. The intangible cost function parameters estimated for each of these three functions are listed in Table 8 below:

	Intangible cost function parameters		
	lo	A	K
High utility limit	3246.48	0.83263	-1.3742
Low utility limit	5084.54	0.233121	11.5330
MLE (Reference)	4349.32	0.362867	6.9818

Table 8 - Intangible cost function parameters encompassing uncertainty range in CIMS

The modelling outputs resulting from the three representations of the intangible cost function are illustrated in Figure 36. The range of uncertainty in CIMS' outputs due to uncertainties in the intangible cost is very narrow, suggesting that CIMS simulations are robust to uncertainties in the intangible costs. This is in stark contrast to uncertainties in the discount rate.

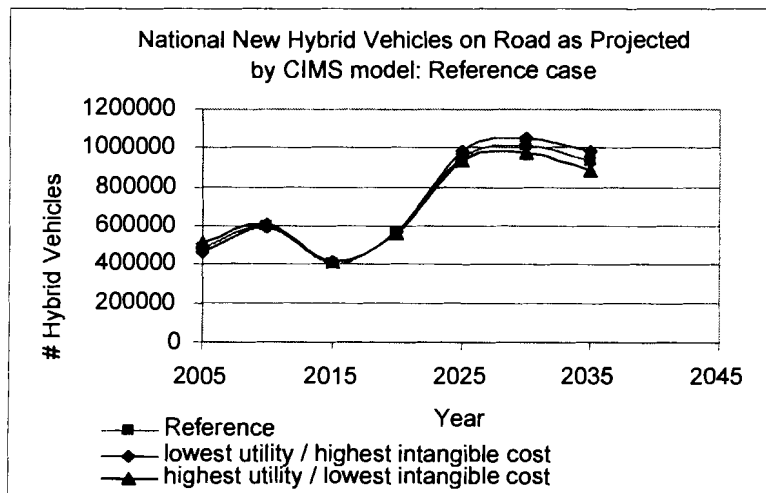


Figure 36 - Sensitivity analysis on i , with CIMS output being national new HEVs

In the next chapter, the results and insights gained from the discrete choice models and the CIMS simulations from the Honda Civic vehicle examples will be used to run sample policy simulations.

4 POLICY SIMULATIONS IN CIMS

Innovations explored in this research include: 1) updating the CIMS parameters to better reflect consumer behaviour; 2) internalizing the intangible cost parameter in CIMS, so that consumer values toward non-monetary attributes change with market conditions; and 3) internalizing the capital cost parameter in CIMS to reflect the declining capital cost for new technologies due to learning.

The Canadian government continues to explore policies to reduce carbon dioxide emissions. Reducing emissions in the transportation sector is one component of this effort. A major part of this reduction will be done through technological changes, where policies will persuade consumers to choose transportation options that are more fuel efficient or have lower greenhouse gas emissions. One such option would be switching from conventional gasoline vehicles to HEVs.

In this study, I included three sets of CIMS policy simulations to address policy questions that the Canadian government may ask in the future regarding technological changes in the transportation sector. The first two policy simulations are “tax on carbon dioxide” and “government subsidy”. The third policy simulation explores regulations that may change HEVs’ non-monetary attributes, such as improvements in service and technological innovations. Such a regulation may be a “renewable portfolio standard” policy, which requires automobile manufacturers to produce and sell a certain amount of alternative fuel vehicles in a given year. Automobile manufacturers may respond to such a regulation by enticing consumers to purchase their HEVs without lowering the financial cost but by improving on the cruising range or warranty. For these policy simulations, I use the 2004 model Honda Civic conventional and HEV versions. The technology

competition structure in the policy simulations are illustrated in Figure 37 below. The technology node affected by the simulations is “Personal Transportation” (shaded box), where the competition in passenger transportation will be split between transit, walking/cycling, gasoline and other vehicle technologies, and HEV (Bold). However, I will focus my discussion on the competition between conventional gasoline vehicles and HEV where appropriate. Note that the information gained from this study can only allow for demonstrating policy simulations, but there are not enough information to evaluate whether one policy is better than another.

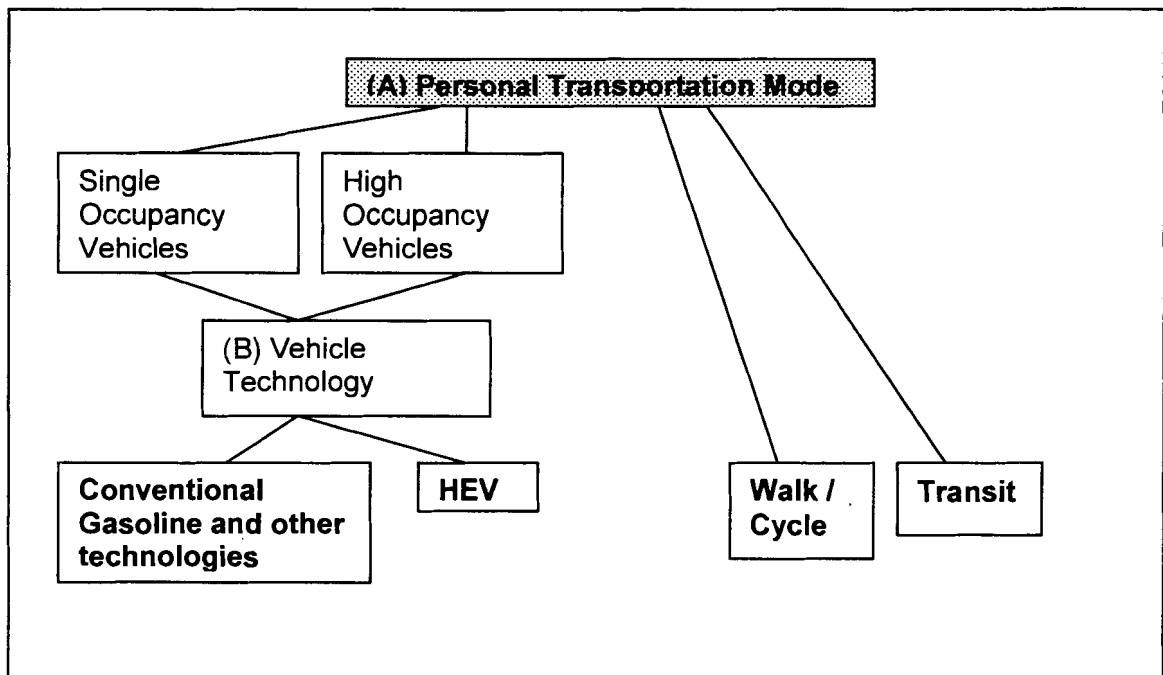


Figure 37 - Policy simulation competition structure

4.1 Tax on carbon dioxide

A tax on carbon dioxide, more commonly referred to as a “carbon tax”, has been the centerpiece of discussion from Canada to the international community as a tool to reduce carbon dioxide emissions in order to meet the obligations imposed by the Kyoto Protocol (Nakata & Lamont, 2001; Wigle, 2001; Hamilton & Cameron, 1994; Piattelli et

al., 2002; Meier & Munasinghe, 1995). One of the major obligations under the protocol is a carbon dioxide emission limit for each country, which, depending on other mechanisms, such as trading of emission credits, has an effect on the size of tax that might be required. For example, the implementation of "global emissions trading", a scheme that is currently under debate under the Kyoto protocol to allow countries to setup a market for importing and exporting their carbon emissions to meet their Kyoto targets, can change the economics of the tax. With emissions trading, countries that emit more carbon dioxide than their Kyoto limit can pay other countries to "accept" their extra emissions. Without emissions trading, all countries are responsible in reducing their own emissions. Thus, in the no emissions trading scenario, the level of domestic tax required to curtail domestic carbon dioxide emissions will be much higher than the emissions trading scenario, because in the latter scenario, the excess emissions can be "paid off". Wigle (2001) estimated that *without* global emissions trading, the level of carbon tax required to comply with the Kyoto Protocol is between \$350US/Tonne CO₂ and \$835US/Tonne CO₂ for Canada. *With* global emissions trading, that figure drops to between \$26 US/Tonne CO₂ and \$114 US/Tonne CO₂.

For the first policy simulation demonstration, I used the new CIMS to simulate the carbon tax effects on the adoption of HEVs. Raising the cost of gasoline will raise the cost of running both HEVs and conventional gasoline vehicles; however, the owners of conventional gasoline vehicles will be more affected by the tax since they consume more fuel per kilometre travelled. Nonetheless, this difference in fuel cost may not be enough to persuade conventional gasoline vehicle owners to switch to HEVs because consumers consider capital costs to be their most important criteria in vehicle choice decisions and HEVs have much higher capital costs than conventional gasoline vehicles.

In total, I produced a package of three different carbon tax simulations using the new CIMS. The first simulation that I produced is “reference”, with no carbon tax. In the second simulation I introduced a carbon tax similar to the low end of Wigle (2001)’s effective carbon tax estimate with global emissions trading, at \$50/tonne CO₂, which converts to an increase of about 12cents/L of gasoline at the pump for drivers. In the third simulation I introduced a carbon tax similar to the higher range of Wigle (2001)’s effective carbon tax estimate without global emissions trading, at \$200/tonne CO₂, which converts to an increase of about 50cents/L of gasoline at the pump for drivers.

The simulation results show that changes in new HEV sales are insensitive to the carbon tax in the years immediately after the tax is introduced. There are very few differences in HEV adoption between the reference simulation and the two simulations that have a carbon tax (Figure 38). Similar to HEV numbers, the new market shares of HEVs are also not significantly affected by the carbon tax (Figure 39). These results suggest that raising fuel prices through a carbon tax policy, at least in the range explored, is ineffective in persuading consumers to switch from conventional gasoline vehicles to HEVs. Closer inspection of CIMS simulation outputs indicate that under the carbon tax policies, current owners of conventional gasoline vehicles are more likely to switch to walking, transit, and carpooling rather than switch to a HEV.

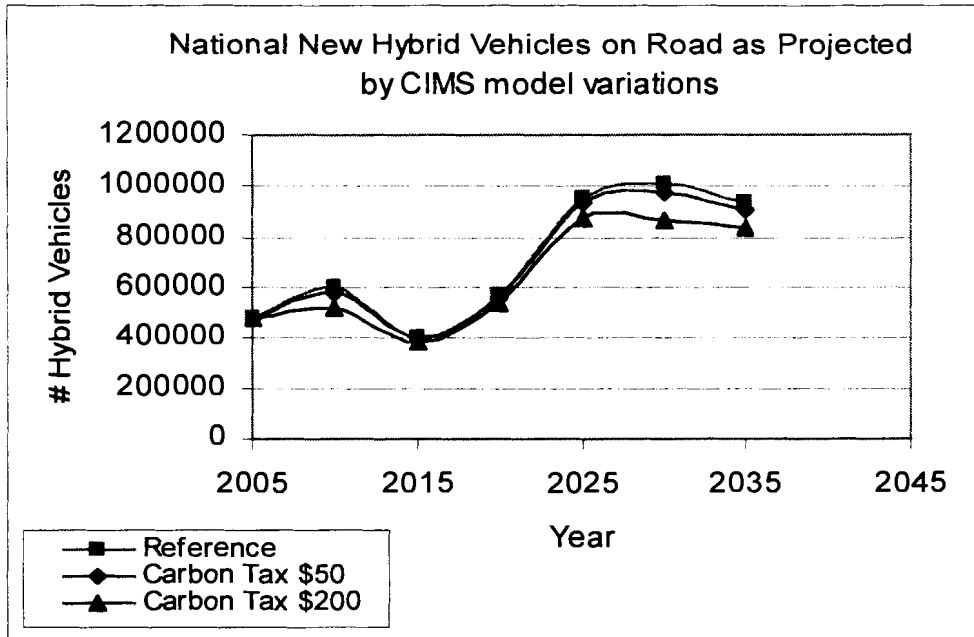


Figure 38 - CO₂ Tax simulation: Indicates that Carbon tax has little effect on HEV adoption by consumers

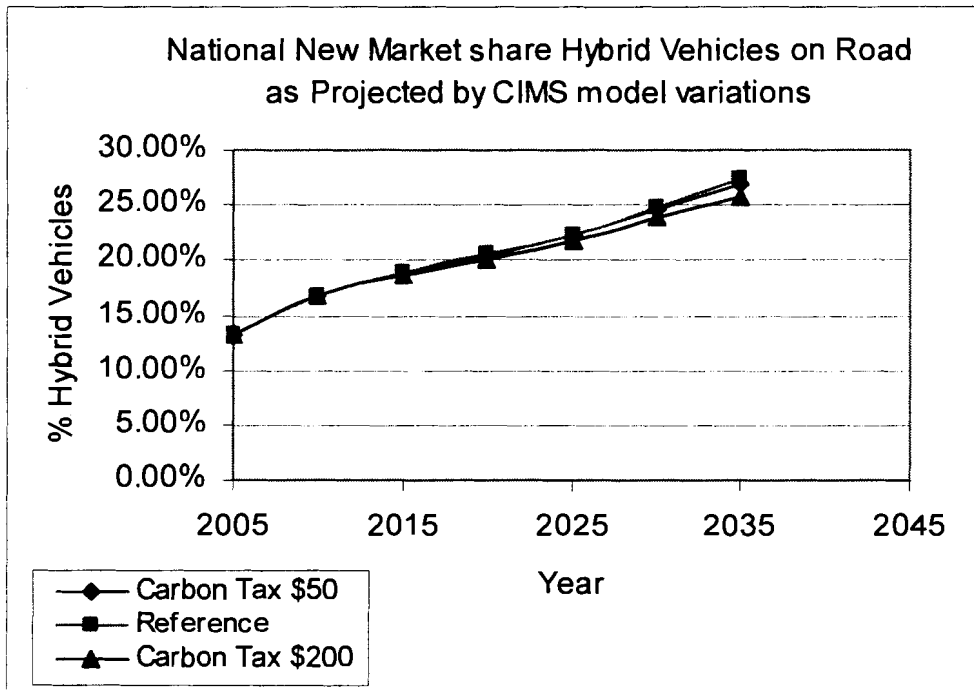


Figure 39 - CO₂ Tax simulation: Indicates that Carbon tax has little effect on the HEV new market shares

4.2 Government subsidies

To achieve Kyoto targets and air pollution goals, there have been experiments with subsidies as a tool to promote the adoption of cleaner energy technologies and fuel efficient, low emission vehicles (Insurance Corporation of British Columbia 2004; Ericsson et al., 2004; Pimentel et al., 2002; Innes, 1995). In this policy exercise, I simulate a subsidy for HEVs in CIMS.

Simulating subsidies in CIMS requires the adjustment of the capital cost function of HEVs to reflect the effect of the subsidy. The results from the vehicle choice experiment indicate that consumers value an amount of subsidy more than the same amount of capital cost reduction of a vehicle, due to consumers valuing gains (ie. subsidies) more than losses (i.e. capital cost). The effect of a \$1 subsidy is equivalent to a \$1.50 to \$2 drop in capital costs depending on the initial market share of hybrid vehicles, and this is adjusted in my inputs to CIMS.

I have simulated a \$1000 subsidy policy and a \$5000 subsidy policy on HEVs in CIMS as a demonstration. A small subsidy of \$1000, similar to the amount given by the Scrap-it-program of British Columbia (2004) is enough to increase the new market share of HEVs by about 3% over the reference "without subsidy" scenario (Figure 40). The effect of this subsidy persists as the market share of HEVs increase, such that a quarter of new vehicles purchased would be HEVs by 2025. Whether subsidy numbers input into CIMS have 1.5 times the effect of capital cost or have 2.0 times the effect of capital cost, this observed trend does not change.

If the capital cost of the HEV is reduced to a level similar to that of a conventional gasoline vehicle through a \$5000 subsidy, the market shares of new HEVs would improve even more dramatically. This amount of upfront subsidy is able to persuade consumers to switch to hybrids almost immediately, leading to a quarter of all new

vehicles purchased to be HEVs by 2010 (Figure 41). Again, whether the subsidy numbers I input into CIMS had 1.5 or 2.0 times the effect of capital cost does not change this observed trend.

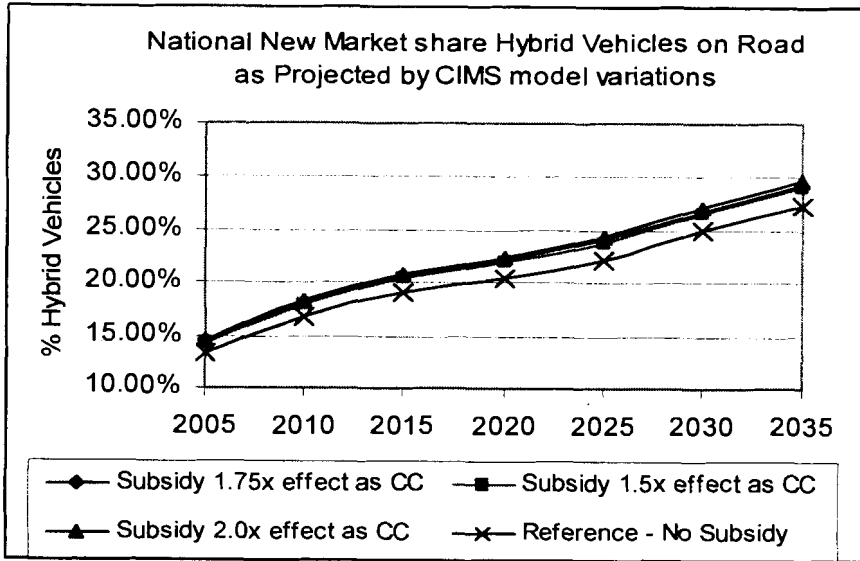


Figure 40 - Subsidy simulation: \$1000

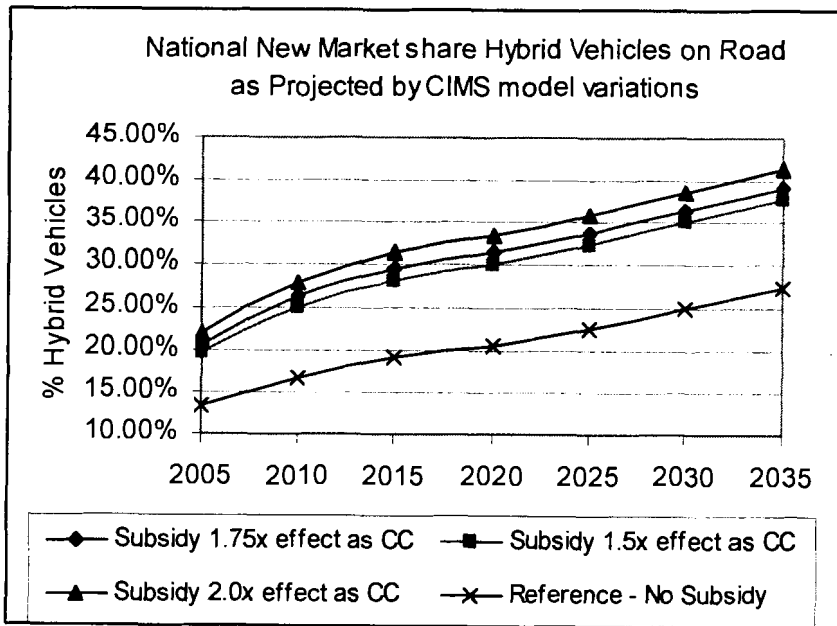


Figure 41 - Subsidy simulation: \$5000

4.3 Changing intangible attributes

Another policy option the government can consider for higher adoption of HEVs is a “renewable portfolio standard”, which is a policy that regulates the minimum amount of HEVs that vehicle manufacturers must sell in a given year. This type of policy has been used most recently in California, where vehicle manufacturers must sell a minimum quantity of lower emission vehicles. Manufacturers might subsidize HEV’s. They might also increase research and development on HEV drive components, such that the cruising range can be extended, or extend the warranty to increase public trust in the HEV technology. Since the subsidy option is already simulated, I added to the analysis by simulating the potential effect on sales of increased cruising range and an extended warranty. I simulated both of these options in CIMS for the province of Ontario as a demonstration.

In the cruising range simulation, I simulated HEVs with a cruising range improvement of 90%; from 19 days to 36 days. Unlike the carbon tax and subsidy policies, cruising range is a non-monetary attribute that must be integrated into the intangible cost function in CIMS. To facilitate this integration, I estimated the intangible cost parameters l_0 , A , and K for each respective cruising range, as presented in Table 9 below.

Cruising Range	l_0	A	K
Reference (19 days)	4349	0.363	6.98
36 days	1919	0.807	-11.5

Table 9 - Cruising Range Policy: Translation to Intangible cost function

The simulation results show that HEV adoption improved by an average of 4% above the reference case for all years. However, a detail tabulation of the results reveal that the increase in HEV market share is not entirely due to existing conventional

gasoline vehicle owners switching to HEVs, but also includes consumers who currently do not own a vehicle switching to HEVs as their primary mode of transportation. Particularly, 9% of transit users and 0.6% of consumers who cycle or are on foot switched to HEVs. This result suggests that CIMS policy simulations targeted at the cruising range of HEVs affects competition at the transportation mode level (“A” in Figure 37), as well as to the vehicle technology competition (“B” in Figure 37). Reducing the intangible cost for HEVs might reduce the weighted average costs for single occupancy vehicles in the transportation mode competition, thus producing the modal shift, whether that was the intention of the policy simulation or not.

Similar to the cruising range policy simulations, I ran a set of simulations for extended warranty coverage from the current standard for new vehicles of 5 to 13 years, which would cover the vehicle for most of its life. The estimated intangible cost parameters I estimated are presented in Table 10.

Warranty	Io	A	K
5 yrs (reference)	4349	0.362	6.981
13 yrs	-2474	0.1	100.45

Table 10- Warranty Policy: Translation to Intangible cost function

The CIMS simulation results show that this warranty increase would improve the new market share of HEVs by 6% on average, for each year of the simulation. Similar to the affects of the cruising range policy, the higher rates of adoption of HEVs are a result of consumers switching from other modes of transportation, such as walking (0.7%) and transit (10%), in addition to current conventional gasoline vehicle owners. Thus, policies affecting warranty coverage was projected to affect competition at the modal level in addition to the vehicle technology level as well under CIMS, similar to the results from policies affecting the cruising range of HEVs.

5 CONCLUSIONS

My research project was one part of a concerted effort by many researchers to introduce realistic consumer decision behaviour into energy economy models. Such improvements should provide more useful modelling outputs for policy makers. My focus was on advancing the hybrid energy economy model, CIMS, such that it can better represent consumer behaviour toward non-monetary characteristics of “evolutionary technologies”. I narrowed my study to HEVs, an evolutionary technology that is promoted internationally as a way to reduce greenhouse gas emissions in the transportation sector. My research added more realistic simulations to CIMS, which, in turn, can enable policy makers to explore realistic options for advancing the adoption of this technology.

I asked three research questions related to consumer decisions between HEVs and conventional gasoline vehicles.

- (1.) Do people place different values in the attributes of HEVs and conventional vehicles?
- (2.) If so, how do these values change with changing market conditions?
- (3.) What do these results suggest for policymaking?

First, this study has found that consumers value the importance of different attributes of vehicles differently, although the order of importance is similar for both HEVs and conventional gasoline vehicles. Specifically, consumers seemed to place the highest importance on capital cost. Second in importance were the non-monetary attributes, such as better cruising range or manufacturer’s extended warranty. Thus, the

current large price gap between HEVs and conventional gasoline vehicles prevented the adoption of HEVs. However, this research has found that once the price of HEV was dropped to a level similar to that of conventional gasoline vehicles, the non-monetary attributes of HEVs and of conventional gasoline vehicles would be a significant deciding factor for consumers.

Second, An innovation of this research over previous studies is that I characterized how consumer decisions on the non-monetary attributes of vehicles change as a function of market conditions. Observations from my study presented evidence that consumers place higher importance on the non-monetary attributes in HEVs as the market share of HEVs increases. Overall, consumers seem to consider different attributes of HEVs to be more or less important than others under different market conditions. To use this information to inform energy economy models, I translated the relationship between consumer behaviour and HEV market shares into the declining intangible cost function in CIMS. Hence, the intangible cost of HEVs is internalized in the CIMS model and changes with market conditions. In previous CIMS versions, the intangible cost of technologies was determined externally and perceived to be static.

To illustrate the difference in simulation results in CIMS due to my study, I have compared the new CIMS, which has the advancements implemented as a result of this research, with the old CIMS, the previous version of CIMS. The adoption of HEVs was significantly different between the two versions, with the new version predicting that consumers would be more willing to switch from conventional gasoline vehicles to HEVs.

Third, using the new CIMS, I ran three sets of policy simulations to demonstrate the implications for policy makers when they make decisions in the future on policies related to HEV technologies. These three policy simulations are “carbon tax”, “subsidy

on HEV”, and “changing intangible attributes”. The simulation results indicated that changing the intangible attributes of HEVs through policy may affect the adoption of HEVs, but also to some extent the choice of transportation mode.

The results of these demonstrations are an indication of what the future will be like if the parameters estimated from my research data are actually true. Uncertainty analysis of the parameters indicated that it is highly likely that other parameter values are also possible. Hence, decision makers who wish to determine the range of possible impacts of their transportation policies should run multiple simulations that encompass other potential parameter values in CIMS for HEVs.

5.1 Recommendation for future research

In this study, I used HEVs exclusively for demonstrating consumer behaviour toward “evolutionary technologies”. However, consumer behaviour towards HEVs may not be the same as for other evolutionary technologies. Thus, my first recommendation is that more research on other evolutionary technologies needs to take place to identify common aspects of consumer behaviour, so that useful generalizations about evolutionary technologies can be made.

My advancements to CIMS are only implemented for the HEV passenger vehicle technology. Specifically, the declining intangible cost function and the dynamic capital cost function have been shown to change the modelling outcomes significantly when compared with the previous version of CIMS. The presented simulations are likely biased pictures of consumer adoption of HEVs, since other new technologies, such as electric vehicles, methanol vehicles, bio-diesel, and hydrogen vehicles were not examined in this research. Hence, my second recommendation would be to capture the

declining intangible cost function and the declining capital cost function for these other potential vehicle technologies to generate more realistic future projections in CIMS.

Finally, my model advancements are based on empirical estimates from stated preference research only, whereas revealed preference research can provide a check on parameter values from real market behaviour. Thus, my third recommendation is that researchers continue to observe the HEV market carefully for the next five years or more, and determine the discrepancy between the CIMS projections and the actual market; perhaps through a “revealed preference” study, where the attributes that consumers find important for HEVs are estimated from actual market data such as sales records. The quantification of this discrepancy could improve the CIMS modelling results to better reflect real world conditions.

5.2 Limitations

I have designed this research such that the results would be as statistically relevant as possible. However, there were limitations. First, the sample size was limited to about 800 survey participants. While this was a representative sample of Canada, more sample might be needed to test for effects within each province. Second, HEVs are a very new technology that most people are not familiar with. Although I have made a sincere effort to educate the survey participants about HEVs, my descriptions might not be adequate enough to fully explain the finer details so that they could give informed answers. Third, the choice sets in the discrete choice experiment were very rich in information, and thus might overwhelm some survey participants. I have limited this problem statistically by randomizing the question orders, but this limitation might still have introduced error into my results. Lastly, the way the questions were asked might have caused some response bias in the data, although I have worded all questions in the survey very carefully to avoid these biases as much as possible.

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APPENDIXES

Appendix I: Screening Survey

Appendix II: Sample Survey

Appendix III: Experimental Design

Appendix I: Screening Survey

Phone Script (2 Pages)

Hello, my name is _____ calling on behalf of Simon Fraser University. We are conducting a survey to learn about Canadians' attitudes and preferences toward new vehicle technologies. Your answers will contribute to the development of future transportation policies across Canada.

The survey consists of a three-minute phone interview, and a fifteen to thirty minute Internet survey. For each completed Internet survey, we will donate two dollars to Unicef. I am not selling anything, and all of your responses will be kept confidential.

Part A - Recruitment

1. Are you, or someone else in your household who is over 19 years of age interested in participating in this survey?

1. Yes

2. No SKIP TO Q8

2. Thank you. Before we continue, may I confirm that you are over 19 years of age?

1. Yes

2. No THANK AND TERMINATE WITH REJECTION REASON 1

Part B - Vehicle Ownership

3. Do you (or your family) own a vehicle?

1. Yes

2. No THANK AND TERMINATE WITH REJECTION REASON 2

4. Does your vehicle run on gasoline?

1. Yes

2. No THANK AND TERMINATE WITH REJECTION REASON 3

Part C - Commuting

5. Do you commute to work or school at least once per week?

1. Yes

2. No THANK AND TERMINATE WITH REJECTION REASON 4

Part D - Internet Access

6. Do you have access to the Internet and an e-mail address?

1. Yes

2. No THANK AND TERMINATE WITH REJECTION REASON 5

Part D - Prepare for Internet Survey

That completes the phone portion of this survey. You will complete the second half of the survey on the Internet.

7. May I please have your e-mail address to send you the website and login ID to access the Internet survey?

Thank you very much for your time. Have a great day/night.

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Part E - Rejection Information

8. Before you go, could you please tell me why you aren't willing to participate in this study?

1. Just not interested,

2. Don't have time,

3. Dislike Internet surveys,

4. Other,

5. Prefer not to say/ REFUSED

Reject Reason 1: I'm sorry, but Simon Fraser University guidelines indicate that we

can

only survey people over 19 years of age. Thank you for your time.

Rejection Reason 2: I'm sorry, but because you don't own a vehicle you don't qualify

for the remainder of this survey. Thank you for your time.

Rejection Reason 3: I'm sorry, but because your vehicle does not run on gasoline you

don't qualify for the remainder of this survey. Thank you for your time.

Rejection Reason 4: I'm sorry, but because you do not commute to school or work more vehicle does not run on gasoline you don't qualify for the remainder of this survey.

Thank you for your time.

Rejection Reason 5: I'm sorry, but because you do not have access to the Internet and

the follow-up survey consists of an Internet questionnaire you don't qualify for the remainder of this survey. Thank you for your time.

Request for Proposals - Due October 15, 2003 6

Script téléphonique (2 pages)

Bonjour, mon nom est ----- . Je vous appelle de la part de l'Université Simon

Fraser. Nous étudions l'attitude et les préférences des canadiens face aux nouvelles technologies automobiles. A travers cette enquête, vous contribuerez au développement

des futures politiques de transport canadiennes.

L'enquête se compose d'un questionnaire par téléphone d'environ 3 minutes, suivi d'un

questionnaire sur Internet qui devrait vous prendre entre 15 a 30 minutes.

Rassurez-vous, je ne veux rien vous vendre et toutes vos réponses seront gardées confidentielles.

Part A - Recrutement

1. Etes-vous, vous ou quelqu'un d'autre dans votre ménage agé de plus de 19 ans, intéressé(e) à participer a cette enquête?

1- Oui

2- Non (Passer directement à la question 8)

2. Merci. Avant de continuer, puisse-je m'assurer que vous êtes bien agé(e) de plus de 19 ans?

1- Oui

2- Non (Merci. Terminer le questionnaire avec "Rejet Raison 1")

Part B- Possesseur du véhicule

3. Possédez-vous (vous, ou votre famille) un véhicule?

1- Oui

2- Non (Merci. Terminer le questionnaire avec "Rejet Raison 2")

4. Est-ce que c'est un véhicule au gazoil?

1- Oui

2- Non (Merci. Terminer le questionnaire avec "Rejet Raison 3")

14

Part C- Trajets

5. Faites-vous les trajets de votre domicile à votre lieu de travail, ou à votre école, au moins une fois par semaine?

1- Oui

2- Non (Merci. Terminer le questionnaire avec "Rejet Raison 4")

Part D- Accès à Internet

6. Avez-vous accès à Internet et une adresse de courriel?

1- Oui

2- Non (Merci. Terminer le questionnaire avec "Rejet Raison 5")

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Part D- En préparation de l'enquête électronique

Cette première partie du questionnaire touche à sa fin. Vous allez maintenant pouvoir

terminer la seconde partie de l'enquête directement sur Internet.

7. Pourrais-je avoir votre adresse de courriel afin de vous envoyer l'adresse du site Internet ainsi que le mot de passe qui vous permettra d'accéder à l'enquête électronique?

Merci beaucoup de votre collaboration. Je vous souhaite une très bonne journée/fin de soirée.

Part E- Information rejetée

8. Avant de raccrocher, pourriez-vous me dire pourquoi vous ne voulez-vous participer à cette étude?

1) Pas intéressé(e),

2) Pas le temps,

3) N'aime pas les enquêtes électroniques,

4) Autres,

5) Préfère ne pas répondre/ REFUS

Rejet Raison 1: Je suis désolé(e), mais les directives d'université de Simon Fraser indiquent que nous pouvons seulement examiner des personnes sur 19 ans. Merci du

temps que vous avez bien voulu nous accorder.

Rejet Raison 2: Je suis désolé(e), mais n'ayant pas de véhicule, vous ne répondez pas

aux critères requis pour participer à cette enquête. Merci du temps que vous avez bien

voulu nous accorder.

Rejet Raison 3: Je suis désolé(e), mais votre véhicule n'étant pas un gazoil, vous ne répondez pas aux critères requis pour participer à cette enquête. Merci du temps que

vous avez bien voulu nous accorder.

Rejet Raison 4: Je suis désolé(e), mais comme vous faites ces trajets moins d'une fois

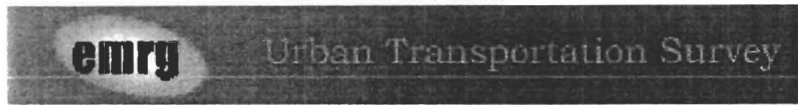
par semaine, vous ne répondez pas aux critères requis pour participer à cette enquête.

Merci du temps que vous avez bien voulu nous accorder.

Rejet Raison 5: Je suis désolé(e), mais comme vous n'avez pas accès à Internet et que

la seconde partie de ce questionnaire se fait sur Internet, vous ne répondez pas aux critères requis pour participer à cette enquête. Merci du temps que vous avez bien voulu nous accorder.

Appendix II: Sample Survey



Hello and welcome to the Urban Transportation Survey !

This survey is conducted as part of a Master's Thesis at the Energy and Materials Research Group in the School of Resource and Environmental Management, at Simon Fraser University (Burnaby, British Columbia).



Thank you for your participation.

Any information that is obtained during this study will be kept confidential.

Knowledge of your identity is not required. So, you will not be required to write your name or any other identifying information on research materials.

Your responses will be analyzed in aggregate, and they will not be identifiable as specifically yours in the results we release.

All information collected during our study will be maintained in a secure location according to Simon Fraser University Ethical Guidelines.

The survey is composed of 7 sections.

- Section 1. Characteristics of Your Current Vehicle
- Section 2. Knowledge of Alternative Vehicles
- Section 3. Information on Alternative Vehicles
- Section 4. Your Vehicle Choices
- Section 5. Views on Vehicle Preferences
- Section 6. Views on New Technologies
- Section 7. Information about Yourself

We will use the information gathered from the survey to assess Canadians' preferences for vehicle technologies that are on the market today or will be available in the future.

Remember that with each completed survey we receive we will donate \$2 to UNICEF.

Your opinions and ideas are important, so please answer every question.

Respondents so far have taken about 25 minutes to complete the survey.

Logging in to our survey below indicates that you understand and are in agreement with our confidentiality provisions.

Please log in with the USER ID and password we have assigned to you.

Login - ID :

Password:

Login!

Section 1: Characteristics of Your Current Vehicle

It is important that you provide an answer or a selection for every question.

1. How many vehicles do you or your family currently own?

2. What is the body type of the vehicle you most often use?

3. What is the make, model, and year of the vehicle you most often use?

Make:	Model:	Year:
<input type="text" value="Honda"/>	<input type="text" value="Civic"/>	<input type="text" value="2004"/>
e.g. Honda	e.g. Civic	e.g. 1992

4. How long have you or your family owned this vehicle?

If you have owned the vehicle for less than one year please enter "0" in years, and enter the number of months.

years, months

5. How much longer do you expect that you or your family will own this vehicle?

If you have less than one year to go please enter "0" in years, and enter the number of months.

years, months / or I don't know how much longer

6. Was this vehicle bought new or used?

- new
- used

7. What was the purchase price for this vehicle when you bought it? *Please use your best estimate.*

8. On average, how much do you pay to maintain this vehicle every year, not including fuel costs?

Please use your best estimate.

9. On average, what are the fuel costs for this vehicle? \$ dollars

10. On average, how far can you drive on a full tank of gas? or Don't know

11. After filling up the tank of gas, on average, how many days could you drive your vehicle before

needing to fill up the tank again? *Please assume normal use.* ⁵

12. How important were the following sources of information when you or your family decided to purchase this vehicle? *Please indicate the importance you place on each source of information.*

	Not at all important	Somewhat important	Very important	Don't know or does not apply
Dealerships: Talking to experts and going for test drives	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>
Magazines or other publications: Reading Consumer Reports, Automotive news, etc	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>
Word of mouth: Talking to your family, friends, and acquaintances	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>
Your own past experience	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>
Other information sources that you might go to when considering to buy a new vehicle.	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>
Please specify: Internet Research				

Next >>

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Section 2: Knowledge of Hybrid Vehicles

How do you believe hybrid electric vehicles (such as the Toyota Prius) compare with standard gasoline vehicles in the following categories? *Please indicate your opinion for each category.*

	Much less than gasoline vehicles	Slightly less than gasoline vehicles	Equal to gasoline vehicles	Slightly more than gasoline vehicles	Much more than gasoline vehicles	Don't know
Reliability	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>
Distance per Fill-Up	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Horsepower and Acceleration	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Fuel Costs	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Purchase Price	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Next >>

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Section 3: Information on Hybrid Electric Vehicles

This section illustrates a hypothetical scenario where *500 of the 1.5 million vehicles sold last year were hybrid electric vehicles*. The sources below contain information about this hypothetical setting.

Please take the time to read the brochure and at least two of the personal statements below. Feel free to browse for as long as you like. Immerse yourself into this hypothetical setting to the best of your ability.

This section sets the stage for the next one.

The links below will open up new windows.

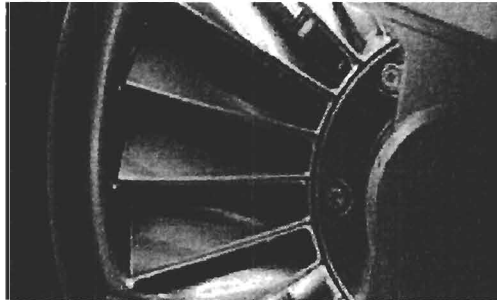
Personal Statements					
	 <p>"I keep track of the latest developments in vehicle technologies."</p>	 <p>"When it comes to vehicles, we are not willing to sacrifice comfort and convenience."</p>	 <p>"I belong to an online chat group for technology enthusiasts."</p>	 <p>"Whenever I learn about a new electronic gadget I try to find a way to test it out."</p>	 <p>"I have the need for speed!"</p>

I'm Ready!

Brochure for Hybrid-Electric Vehicles

Safe, reliable, efficient and affordable to service. It's no wonder 500 of the 1.5 million vehicles sold last year were hybrid electric vehicles.

Powered by an advanced system that combines an ultra-efficient gasoline engine with a battery-powered electric motor, hybrid electric vehicles have all the performance of conventional cars while running much cleaner. And that's not all .



PERFORMANCE The gasoline / electric hybrid engine provides powerful and smooth acceleration when you need it most: from starting up to climbing hills.

When coasting or applying the brakes, the battery-powered electric motor actually becomes a generator, recharging as you drive by converting forward momentum into electrical energy. The energy is stored in the system's Nickel Metal Hydride (NiMH) battery pack and re-used to assist the gasoline engine when you accelerate.

EFFICIENCY The hybrid vehicle's advanced system can achieve nearly 2.5 times the average fuel efficiency of conventional vehicles - this translates into a lot fewer smog-forming and greenhouse gas emissions.



SAFETY AND CONVENIENCE The hybrid vehicle combines cutting-edge engine technology innovations with the safety features you have come to expect from conventional vehicles. Plus, no new maintenance schedules to learn. Your local dealer can provide all your servicing needs. Go for a test drive today, and find out what you've been missing!



(Close this window to go back to the survey)



I keep track of the latest developments in vehicle technologies.

I first heard about the "car of the future" a few years ago at a convention in Europe. Then I saw one for myself during a demonstration project in Ottawa. When I found out that the federal government had started a rebate program to encourage Canadians to buy this type of vehicle I jumped at the chance. I wanted to be the first person on my block to drive a hybrid electric vehicle .

I've had the vehicle for a few months now, and I enjoy its smooth acceleration and great gas mileage. I was very intrigued by the feedback system between the gasoline engine and the battery-powered electric motor. The vehicle runs on electricity whenever I press the gas pedal. When coasting or applying the brakes the electric motor becomes an electricity generator. This electrical energy is stored in the battery pack and helps the gasoline engine when you accelerate.

I find this vehicle safe, reliable, and very efficient. The dealer was not very good at explaining how to use the instrumentation panel, but it was fun to discover this on my own! I'm really excited about being one in five thousand Canadians driving this type of vehicle.



When it comes to vehicles, we are not willing to sacrifice comfort and convenience.

When we first started shopping around for a new vehicle we looked at hybrid electric vehicles at our local dealer, fully intending to buy one if it was suitable. Instead, we found that there were many features about the vehicle that we didn't like. First of all, the seats were hard and uncomfortable on my husband's back.

Second, the vehicle is designed to save the most gasoline on city driving and most of our driving is on highways. The more we thought about this, the more we realized what a pain it might be. Third, my spouse and I really enjoy manual transmission and the hybrid electric vehicle only comes in automatic.

We know that hybrid electric vehicles are much better for the environment than gasoline vehicles but we value our convenience. Plus, we once owned a car that caused lots of pain and chiropractor bills and will not do that again. So, we bought the most efficient gasoline-powered vehicle we could find and are very happy with our decision.

emrg

Urban Transportation Survey



I belong to an online chat group for technology enthusiasts.

I bought a hybrid electric vehicle two months ago. So far, I am enjoying the ride. The car is great in terms of performance and reliability. I knew I would get good gas mileage, but I have actually managed to improve the vehicle's efficiency by using the feedback from the instrumentation panel, which shows me how the gasoline engine and the battery-powered electric motor work together.

I can't park it anywhere without someone asking me about the car. I've also allowed several friends and colleagues to test drive it so they can see that it handles very much like a normal 5-speed.

I predict that within the next few years many more Canadians will drive hybrid electric vehicles. I'm happy about being among the first 450 Canadians to switch to this technology!



Whenever I learn about a new electronic gadget I try to find a way to test it out.

When I found out about the hybrid electric vehicle demonstration project in town, I applied to be considered eligible for a test drive. I test drove it and it is pretty much like a normal car. Well, I mean that its performance was about the same as a normal car. Acceleration was powerful and smooth, especially when starting up and zipping around the hilly parts of town.

The system combines a gasoline engine with a battery-powered electric motor, which is supposed to improve gas mileage by up to 2.5 times that of regular cars. The instrumentation panel lets you know about your mileage statistics as you're driving. This might be a distraction at first, but it's a really neat feature.

I really enjoyed the test drive. I think I know what my next vehicle purchase will be. I'd be pretty excited about being among the first 450 Canadians to switch to this technology!



I have the need for speed!

I went and bought a hybrid electric vehicle just the other day from the dealer. After all, it seems like a few Hollywood superstars are driving these around, so I'm quite enthusiastic about seeing what all the fuss is about.

To be honest, it does meet most of my everyday commuting needs to and from work - a good replacement for my old vehicle. It drives quietly, and it keeps me cool in the traffic jams with the A/C - a big bonus considering that my old vehicle had no A/C, and I had to sit in the heat.

However, it was no show stopper. I miss the sweeet noise that once came from my old car when I revved it up. This new vehicle runs quietly, and everything is automatic - even the transmission. I swear that I can hear a pin drop! I've never owned a car where I can hear myself breathe!

In the driver's seat, I feel more like an operator, rather than being part of the car. There is absolutely no intimidation factor that can impress my friends, nor is there enough power to let me burn some rubber when the green light flashes. This is really too bad!

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Section 4: Your Vehicle Choices

Before proceeding, please read the following instructions:

For the next section, consider that you are in the future as was just described.

You will be asked to make a series of **18 vehicle comparisons**. Each comparison involves choosing between two vehicles. Select the vehicle that you would most likely choose as your next vehicle purchase, if your choices were limited to these two.

Assume that both vehicles have the same body types and are similar in appearance to the vehicle you currently own, except for the information stated.

The 18 comparisons will look very similar, but there are a few differences. ***Please consider each comparison independently of the others, and read each one carefully.***

Proceed

Section 4: Your Vehicle Choices

0 more comparisons to go...

If these were the only vehicle options available to you, which one would you choose?

	Gasoline Vehicle	Hybrid Electric Vehicle
Purchase Price (Does not include government taxes or subsidies)	\$16000	\$27200
Subsidy on Purchase Price (The subsidy is given by the Canadian Government 6 months after purchasing the vehicle as a rebate)	No subsidy	\$800
Fuel Cost / Week	\$30	\$20
Km you can drive your car between refueling	400	600
Warranty Coverage Period (Includes power train and batteries)	5 years, 100,000 Km (60,000 Miles)	10 years or 163,000 Km (100,000 Miles) / 10 ans ou 163,000 Km (100,000 Milles)
I would choose this vehicle:	<input checked="" type="radio"/>	<input type="radio"/>

Next >>

Section 5: Views on Vehicle Preferences

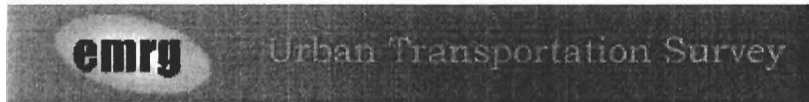
Assume that you or your family is considering buying a new vehicle to meet your current, everyday tra needs. List the three makes and models that you would consider for your next vehicle purchase (e.g., Ford Explorer, etc.).

Honda Accord

Ford Mustang

Toyota Echo

Submit



89.5% Complete

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Section 5: Views on Vehicle Preferences (Continued)

1. Assume that you or your family has decided to purchase a Honda Accord, and the Honda Accord is available as a hybrid electric vehicle and as a conventional gasoline vehicle.

If both are comparable in price and performance, which vehicle type would you be most

likely to purchase Gasoline vehicle, or hybrid electric vehicle

2. Assume that you or your family has decided to purchase a Ford Mustang, and the Ford Mustang is available as a hybrid electric vehicle and as a conventional gasoline vehicle.

If both are comparable in price and performance, which vehicle type would you be most

likely to purchase Gasoline vehicle, or hybrid electric vehicle

3. Assume that you or your family has decided to purchase a Toyota Echo, and the Toyota Echo is available as a hybrid electric vehicle and as a conventional gasoline vehicle.

If both are comparable in price and performance, which vehicle type would you be most

likely to purchase Gasoline vehicle, or hybrid electric vehicle?

4. If you or your family has decided to buy a hybrid electric vehicle, but the vehicle is not

available as a Honda Accord, Ford Mustang, or Toyota Echo, how likely are you to consider other makes and models

Very Likely Likely Unlikely Very Unlikely

Next >>



93% Complete

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Section 5: Views on Vehicle Preferences (Continued)

5. Assume that your primary vehicle has reached the end of its life. You and your family are now considering buying a new vehicle that will serve the same purpose.

For example, if you use your primary vehicle to go to work, this new vehicle will also be used to take you to work.

Would you consider purchasing a new vehicle with a body type that is different than your primary vehicle?

"Body type" refers to the type of vehicle, e.g., mid-size car, SUV, truck, etc.

Yes ▾

If "Yes", would you consider the following body types? *If "No", Skip to question 6*

	Yes	No
Mid-Size Car	<input type="radio"/>	<input type="radio"/>
Full-Size Car	<input type="radio"/>	<input type="radio"/>
Truck	<input type="radio"/>	<input type="radio"/>
SUV	<input type="radio"/>	<input type="radio"/>
Mini-Van	<input type="radio"/>	<input type="radio"/>

6. Assume the same situation as above (your primary vehicle has reached the end of its life). You and your family have decided to buy a **hybrid electric vehicle** to replace your primary vehicle.

Unfortunately, you have found out that hybrid electric vehicles are not available in the body type of the vehicle you are replacing.

Please indicate if you would consider switching to the following:

	Yes	No
Mid-Size Car	<input checked="" type="radio"/>	<input type="radio"/>
Full-Size Car	<input type="radio"/>	<input checked="" type="radio"/>
Truck	<input type="radio"/>	<input checked="" type="radio"/>
SUV	<input type="radio"/>	<input checked="" type="radio"/>
Mini-Van	<input type="radio"/>	<input checked="" type="radio"/>

7. Assume that your municipality requires that you hold a permit in order to operate conventional gasoline vehicles. You are not required to hold a permit to run alternative fuel or very low emissions vehicles, such as hybrid-electric, hydrogen fuel cell, natural gas vehicles, etc.

Assume that your car insurance plan currently entitles you to a gasoline permit to operate the conventional gasoline vehicle(s) you currently own, at no extra charge. You can transfer this permit to other new vehicle owners or to your next vehicle purchase.

What is the one-time lump sum in Canadian dollars that you would be willing to accept to give up your gasoline permit for your primary vehicle?

\$

What is the one-time lump sum in Canadian dollars that you would be willing to accept to give up your gasoline permit for your second vehicle?

\$ or Not Applicable (eg. I don't have a second vehicle)

What is the one-time lump sum in Canadian dollars that you would be willing to accept to give up your gasoline permit for your third vehicle ?

\$ or Not Applicable (eg. I don't have a third vehicle)

Section 6: Views on New Technologies

1. Please indicate your views on purchasing new technologies on the following scale. "New technologies" include items such as mobile phones (cellular phones), DVD players, alternative fuel vehicles, etc. Please check the best answer for each statement.

I would buy the new technology when most people have made the switch and it becomes inconvenient to own the old technology	I would buy the new technology when it has proved itself and maintaining it is not problematic	I want to be the first person in my neighbourhood, in my family, or among my circle of friends to buy the new technology
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

2. Please indicate if you agree/disagree with the following statements:

	Agree	Disagree	don't know / doesn't apply to me
I would be willing to spend a bit more money to buy a technology that is ecologically friendly	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would be willing to spend a bit more money to buy a technology that is ecologically friendly provided the new technology benefited me in some way	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Next >>

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Section 7: Information about Yourself

Thank you for participating in our survey.

Below are questions related to demographics. Your answers will allow us to draw baselines in our stu

Like your answers in previous sections, the information contained in this section will remain anonymou aggregate the information upon collection, and the data will not be traceable back to you.

What is your age group?

What is your family annual income?

What is your household size?

In which region of Canada are you located?

What is your gender?

What is your highest level of education completed?

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Thank You!

The Urban Transportation Survey is now complete. Thank you for your participation.

The survey results will be used for academic research at the Energy and Materials Research Group of the School of Resource and Environmental Management at Simon Fraser University. It is our goal to advise the government of Canada on policies that are socially, economically, and scientifically sound. These policies will contribute towards a sustainable future.

If you are interested in our results, please visit this website in **August 2004**.

If you have any comments about the survey, please fill in the box below and click on "Add Comments".

If you have any specific questions or concerns, you can also contact the main researchers behind this project at the Energy and Materials Research Group at Simon Fraser University:

Via Email: emrgsrvy@sfu.ca

Add comments and/or Quit

Appendix III: Experimental Design

Description of Survey Design for 36 Fractional Factorial

- Number of profiles (i.e., choice sets): 18
- Main effects: not independent
- Degrees of freedom: 5
- Two factor interactions accommodated: 0

This design plan will not allow the estimation of any two-factor interactions independent of main effects and each other.

Correlation Coefficients

a (Order 1)	1											
a (Order 2)	0	1										
b (Order 1)	0	0	1									
b (Order 2)	0	0	0	1								
c (Order 1)	0	0	0	0	1							
c (Order 2)	0	0	0	0	0	1						
d (Order 1)	0	0	0	0	0	0	1					
d (Order 2)	0	0	0	0	0	0	0	1				
e (Order 1)	0	0	0	0	0	0	0	0	1			
e (Order 2)	0	0	0	0	0	0	0	0	0	1		
f (Order 1)	0	0	0	0	0	0	0	0	0	0	1	
f (Order 2)	0	0	0	0	0	0	0	0	0	0	0	1

Eigenvalues

a (Order 1) 1
a (Order 2) 1
b (Order 1) 1
b (Order 2) 1
c (Order 1) 1
c (Order 2) 1
d (Order 1) 1
d (Order 2) 1
e (Order 1) 1
e (Order 2) 1
f (Order 1) 1
f (Order 2) 1

All the Eigenvalues are equal to 1, therefore the design is orthogonal.

Design Matrix

000000
011211
022122
101112
112020
120201
202210
210121
221002
002101
010012
021220
100222
111100
122011
201021
212202

Choice Sets

Where levels 1, 2 and 3 correspond to 0, 1, and 2 in the design matrix, respectively.

Gasoline Car
a a2
b b1
HEV
c c2
d d2
e e2
f f3

Gasoline Car
a a2
b b2
HEV
c c3
d d1
e e3
f f1

Gasoline Car
a a3
b b2
HEV
c c3
d d3
e e1
f f3

Gasoline Car
a a3
b b3
HEV
c c2
d d1
e e1
f f3

Gasoline Car
a a1
b b1
HEV
c c1
d d1
e e1
f f1

Gasoline Car
a a2
b b3
HEV
c c1
d d3
e e1
f f2

Gasoline Car
a a1
b b2
HEV
c c2
d d3
e e2
f f2

Gasoline Car
a a1
b b2
HEV
c c1
d d1
e e2
f f3

Gasoline Car
a a1
b b3
HEV
c c2
d d3
e e3
f f1

Gasoline Car
a a2
b b1
HEV
c c1
d d3
e e3
f f3

Gasoline Car
a a2
b b2
HEV
c c2
d d2
e e1
f f1

Gasoline Car
a a3
b b3
HEV
c c1
d d2
e e2
f f1

Gasoline Car
a a1
b b1
HEV
c c3
d d2
e e1
f f2

Gasoline Car
a a3
b b1
HEV
c c2
d d1
e e3
f f2

Gasoline Car
a a3
b b1
HEV
c c3
d d3
e e2
f f1

Gasoline Car
a a3
b b2
HEV
c c1
d d2
e e3
f f2

Gasoline Car
a a2
b b3
HEV
c c3
d d1
e e2
f f2

Gasoline Car
a a1
b b3
HEV
c c3
d d2
e e3
f f3