SIMULATING MARKET TRANSFORMATION DYNAMICS USING A HYBRID ENERGY ECONOMY MODEL: A LOOK AT THE ADOPTION OF HYDROGEN FUEL CELL VEHICLES

by

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Ethics Approval

The author, whose name appears on the title page of this work, has obtained human research ethics approval from the Simon Fraser University Office of Research Ethics for the research described in this work, or has conducted the research as a member of a project or course approved by the Ethics Office.

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ABSTRACT

Policymakers committed to inducing technological change need information about the likely effects of alternative policies, potential adoption rates of clean technologies, and costs to society in the long run. My goal was to use a "hybrid" energy economy model (CIMS), which combines a degree of behavioural realism, technological explicitness, and economy-wide feedback capabilities, to develop policy-relevant information about dynamics in consumer preferences for hydrogen fuel cell vehicles (HFCVs).

I designed a survey to investigate whether people's valuations of HFCVs change with increased market penetration (the "neighbour effect"). I used the survey results to build discrete choice models, which showed capital cost and refuelling convenience as key influences on consumers' choices and the importance of stated attitudes towards new technologies. However, I found no evidence of the neighbour effect. Rather than rule out this factor in consumer decisions regarding HFCVs, I attribute the result to limitations of the experimental design.

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CHAPTER 1 INTRODUCTION

1.1 Sustainable Policymaking in the Face of Uncertainty

Canada has committed to reducing greenhouse gas (GHG) emissions within the international policy framework, but, based on current trends, Canadian GHGs are forecasted to increase by 32% above 1990 levels by 2010 (Natural Resources Canada 1999). Transportation is among the most GHG intensive sectors, accounting for 25% of national emissions, and projections indicate it will remain that way (Jaccard et al. 2002). On average, transportation accounts for about half of personal GHG emissions, the majority of which come from single occupancy vehicle travel (Horne 2003). Emissions from passenger cars and light trucks in urban centres are on the rise, and studies indicate that trends in vehicle sales and person kilometres traveled are outweighing and will likely continue to outweigh any gains in fuel efficiency in the near future (Natural Resources Canada 2002).

Effective government policies directed at the transportation sector could have dramatic effects on vehicle and fuel demand, yielding considerable environmental benefits. At present, the balance of policy responses to reduce GHG emissions, in general, and in the urban passenger transportation sector, specifically, rely on information and subsidies to encourage and facilitate sustainable personal transportation choices. These policy responses do not require government coercion on producers or consumers, and have not caused visible negative responses from the supply or demand side, thereby minimizing political risk. However, the administrative costs the federal government incurs to finance these policies are not insignificant (Government of Canada 2003). More importantly, some researchers indicate that transforming urban passenger behaviour warrants strong policy intervention if GHG emissions reduction goals are to be achieved (see for example, Jaccard et al. 2003; Greene and Plotkin 2001, Ewing and Sarigöllü 2000).

Researchers stress the importance of technological change and policymaking in attaining sustainability goals (Grubler et al. 1999, Azar and Dowlatabadi 1999, Duke and Kammen 1999, Toman 1998). First, the stock of technologies in an economy determines its impact on the environment. Technology choices can evolve in a way that exacerbates this impact or constrains it. Second, policymaking can stifle or create incentives for innovation and diffusion of clean technologies, depending on the choice of policy instrument (Kerr and Newell 2001). The right policy design can help clean technologies reach a critical threshold of market penetration or consumer acceptance, and, in this way reduce the economic impact of meeting an environmental goal. Experiences in industrialized countries with voluntary policy instruments indicate that, unless the threat of mandatory policies exists, volunteerism generally provides weak incentives for technological change or changes beyond what would have occurred anyway (Organization for Economic Cooperation and Development 2003). Researchers suggest that inducing technological change would require the use of more coercive policy instruments, such as market-based instruments, fiscal policies, and regulations (Moxnes 2004, Kerr and Newell 2001, Jaffe et al. 2001, Pilkington 1998).

In the context of Canadian climate change policy, the federal government might play a role in creating a market for less GHG emitting vehicle technologies and fuels (Government of Canada 2002). However, taking part in market transformation dynamics would require substantial and sustained investment, which carries significant political and economic risk. These risks relate to the highly uncertain dynamics associated with new technologies, both on the producer and on the consumer side. Also, the federal government would require some understanding of the non-financial costs consumers might face as a consequence of policy implementation. In sum, policymakers committed to inducing profound technological change need a better understanding of what the appropriate policies are, what the potential adoption rates of clean technologies are, and how much these policies will cost society in the long run.

Models that simulate the interaction between energy and the economy can be useful tools to evaluate the social costs and expected outcomes of alternative policies. However, definitions of costs, representation of consumer behaviour, technological explicitness, and economy-wide feedback capabilities vary among model specifications, leading to different results to the same policy problem (Jaccard et al. 2003). Instead of being useful to decision-makers, results from different simulation exercises can further confuse them. In the next section, I provide a brief discussion on the differences among approaches to energy-economy modelling to clarify the reasons behind the discrepancies in their modelling outcomes. The discussion concludes with a description of an approach to energy-economy modelling that can assist policymakers in designing policies aimed at inducing technological change.

1.2 The Challenge of Energy-Economy Modelling

Two traditional approaches to energy-economy modelling exist: top-down modelling, grounded in a macroeconomic framework, and bottom-up modelling, which is highly disaggregated and explicitly represents a series of technologies. The philosophies underlying the two approaches differ; that is, these models were historically designed to address different questions (Jacobsen 1998). However, analysts today use both types of models to assess the costs of reducing GHG emissions from the economy. Traditionally used by economists, top down models use a series of equations to depict aggregate relationships between costs, market shares of economic inputs (energy, materials, labour, and capital), and sectoral or economy-wide outputs, all within a macroeconomic setting. Analysts estimate these relationships from time series of data for energy prices and demand. Top-down modelling uses two indices to represent the evolution of technologies in an aggregate way. "Elasticities of substitution" (ESUB) capture the price-driven substitution between inputs and between energy forms. The "autonomous energy efficiency index" (AEEI) captures improvements in an economy's energy efficiency that are not induced by price changes. Because both indices are based on revealed market information, top-down models contain a degree of behavioural realism, i.e., they implicitly incorporate changes in consumer preferences. The costs of reducing GHG emissions from energy intensive activities amount to the price signal (e.g., carbon tax or upstream cap and trade system) needed to attain a given GHG emissions target. Since the assumption is that firms and consumers would have already optimized their position in the reference case, any other action implies a cost, which partly explains why GHG abatement costs resulting from top-down modelling exercises tend to be high in comparison to results from bottom-up models (Weyant and Hill 1999, Jacobsen 1998).

Critics question the validity of top-down models' behavioural parameters to apply to a future defined by GHG constraints, and how this might affect these models' capacity to portray technological change (Grubb et al. 2002, DeCanio and Laitner 1997). Top-down models assume that consumers make decisions based on past and current information and not expectations about the future. Thus, traditional top-down models cannot accommodate for the impacts of widespread commercialization of new low-GHG emitting technologies or the possibility that preferences for these new technologies might change in the long run. In response to this criticism, a few modellers have made attempts at endogenizing technological innovation and diffusion of new energy technologies (Loschel 2002, Jacobsen 2001, Carraro and Galeotti 1997). Their approaches have focused on incorporating spill-over effects from subsidies to research and development (R&D), subsidies to known best available technologies, and economies-of-learning. [1]

Engineers, planners, and environmental advocates are the primary users of bottom-up models. They use these tools to assess the levels of GHG emissions associated with alternative constraints regarding energy efficiency, fuel use, equipment, and land use (Jaccard et al. 2003). Bottom-up models can simulate sector or technology-specific policies, as specified by these constraints. Bottom-up models are detailed in their portrayal of energy technologies, and often include both present technologies and expectations about future technologies in their simulations. Often, differences in discounted financial costs alone determine the market shares for competing technologies, which means that bottom-up models assume that two technologies that provide the same service are perfect substitutes except for their financial cost (and

[1] An" experience curve" portraying the rapid decline in financial costs of an emerging technology as a function of changes in production levels and early operating experience can describe economies-of-learning (also called learning-by-doing). As the technology matures efficiencies taper off (Grubb et al. 2002).

emissions). These models cannot characterize the factors inhibiting the adoption of less-polluting technologies with lower financial costs than the dominant, polluting technology, which is an issue that is widely documented (see, for example, Sutherland 1996). The costs of GHG emissions reduction policies only include changes in the costs of operating the stock of technologies. Thus, bottom-up models do not capture the full social cost of switching among technologies, and tend to underestimate the costs of a given climate change policy (Jaffe and Stavins 1994). In reality, firms and individuals are not simple financial optimizers – their technology choices take into account qualitative differences between technologies and perceptions about risk. From a consumer's perspective, two technologies that provide the same service are not necessarily perfect substitutes. Consumers tend to view new technologies, especially those that require long payback periods, as risky in terms of both safety and investment. Therefore, consumers might see a value in delaying these risky investments until they are better informed. Economists call this "option value" (Pindyck 1991). In addition, although clean or less-polluting technologies provide an equivalent quantitative energy service, they might not provide the same service qualities that make conventional technologies more appealing. For example, even if public transit were reliable, convenient, accessible, and inexpensive, consumers might still prefer driving their expensive and GHG-emitting cars for the sake of additional comfort and freedom. Economists call the value a consumer receives beyond the financial costs of a given technology "consumers' surplus". As well, consumers might not have the same level of access to or face the same financial costs of a given technology across the economy. All these "intangible costs" are important to account for when considering the adoption potential of low-GHG emitting technologies in the long run.

To take advantage of the relative strengths of the two types of energy-economy models some analysts have begun using a hybrid modelling approach (Jaccard et al. 2003, Frei et al. 2003, Jacobsen 1998, Manne and Richels 1994, Manne and Wene 1992). Hybrid energy-economy models are technologically explicit, incorporate behavioural realism consistent with revealed market behaviour, and capture macro-economic effects of alternative policies. This combination of capabilities is particularly useful to analysts seeking to evaluate the potential of policy options to cause profound technological change in the long run (Jaccard et al. forthcoming). But, unless the model formulation recognizes the existence of dynamics in technology adoption, policy modelling exercises could underestimate the long-term potential of low GHG emitting technologies to achieve significant market shares. Specifically, modellers must address two key sources of uncertainty, (1) the way preferences for technologies can change and (2) the way financial costs for new technologies can evolve. A better understanding of both uncertainties can be useful for policymakers in developing expectations about the effectiveness of policies aimed at increasing the market share of low GHG emitting technologies in the long run.

1.2.1 Uncertainties in Technological Change

For reasons that are beyond the full control of political-economic systems, consumers' preferences for emerging and unconventional technologies can change in the long run (Jaccard et al. 2003, Macauley et al. 2002, Norton et al. 1998, DeCanio and Laitner 1997). This means that consumers' surplus and option values for new technologies are not static. Preferences can change for a variety of reasons, some of which include: learning from others' experiences with the technology, new information about a technology's safety and reliability, increased concern for the environment, and changes in availability of the technology relative to the availability of conventional alternatives. Policy packages themselves can also influence preferences by making certain technologies more or less available to consumers. For example, California's vehicle emission standards, launched in 1990, require car manufacturers to produce and sell a certain market share of low-emission cars by 2010 (California Air Resources Board 2001). This policy has made alternative fuel / vehicle technologies viable options for consumers in California, as manufacturers market these vehicles aggressively. Hybrid modellers can help policymakers by using empirical evidence to explore how consumer preferences can influence the adoption rates of low GHG emitting technologies in the long run, and whether policies can be designed in a way that increases the market penetration of these technologies without causing huge losses in consumers' surplus.

Uncertainty about technological innovation and commercialization implies that future financial costs of new technologies can be under - or overestimated today. For example, innovations in the transformation of fossil fuels into hydrogen and subsequent storage of by-products in geological media can dramatically reduce the financial cost of hydrogen-based technologies like fuel cells. Direct subsidies, tax breaks, and other government policies can help drive down the costs of producing new technologies, moving them from the innovation stage to the commercial stage. Although such policy efforts can reduce near-term uncertainties in technological development, long run effects - 20 years or more from now - remain highly uncertain. One approach to incorporating the evolution of financial costs of new technologies in hybrid modelling is to use "experience curves", which I referred to earlier. Trends based on the commercialization and diffusion of conventional technologies, and some studies on emerging technologies, indicate that the rate at which capital costs decline in response to learning on the supply-side varies (Azar and Dowlatabadi 1999, Duke and Kammen 1999). The variation depends on attributes of the technology and on the feedback loop between supply and demand. Experience drawn from the first few units of production can reduce financial costs to the point of creating a niche market (Adamson 2003). But, further declines in capital costs require continued market acceptance, which, in turn, is dependent on the ability of producers to make the technology more attractive, and the technology's increased visibility (Adamson 2003).

In sum, hybrid energy economy models that accommodate endogenously the dynamics in consumer preferences and the effects of production efficiencies on new technologies' financial costs can provide a realistic representation of long-run technological change. Policymakers committed to inducing technological change will find the results of modelling exercises using these types of hybrid models valuable. The goal of the research described in this paper is to use a hybrid energy-economy model (CIMS) to look at the dynamics of technological change, with a focus on representing long-run changes in consumer preferences for a new vehicle technology.

1.3 Description of CIMS

CIMS, housed at the Energy and Materials Research Group (EMRG) at Simon Fraser University, is an integrated, technology-specific energy-economy model, including components to incorporate behavioural realism. The model simulates the interaction between energy flows and representative economic sectors by linking three modules: energy demand, energy supply and the macro-economy. The three modules can also run individually. A single "simulation run" is complete once energy prices resulting from the dynamic interplay among modules converge. The convergence procedure repeats for every five-year period of the run (Jaccard et al. 2003).

CIMS tracks the evolution of technology stocks as a function of changes in the demand for services the technologies fulfil. An example of a service is "person kilometres travelled," which represents the demand for technologies used for personal mobility. In each period of the run, CIMS accounts for technology retirements, retrofits, and new purchases. Demand for new stock depends on capital stock turnover, the assessment of current stock, and expectations regarding growth in service demand. CIMS allocates new market shares for each technology by simulating competition at each service node according to the following logistic relationship:

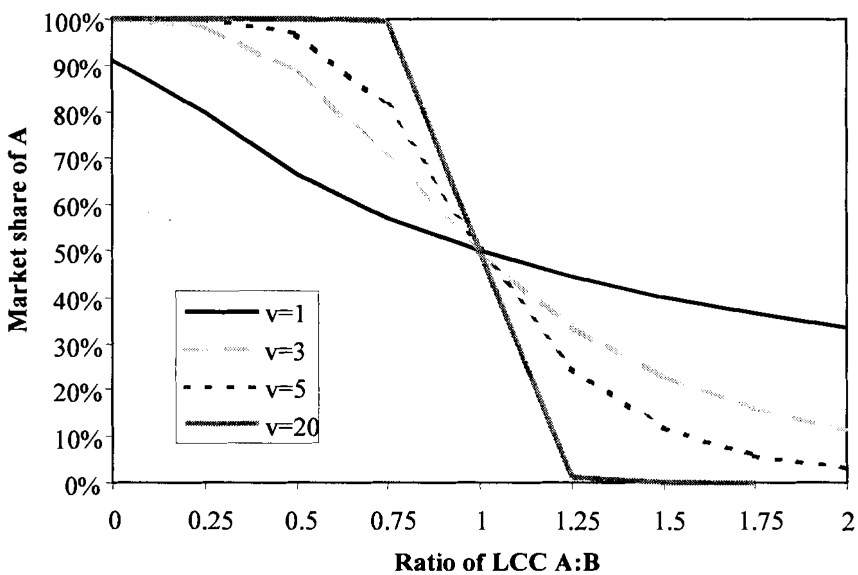
$$MS_j = \frac{\left[CC_j * \frac{r}{1-(1+r)^{-n}} + MC_j + EC_j + i_j\right]^{-v}}{\sum_{k=1}^{K}\left\{\left[CC_k * \frac{r}{1-(1+r)^{-n}} + MC_k + EC_k + i_k\right]^{-v}\right\}}$$

Equation 1

In this equation, MS_j is the market share of technology j, CC_j is the capital cost, MC_j is the maintenance and operation cost, and EC_j is the energy cost. The equation contains three behavioural parameters aimed to capture aspects of decision-making that are not directly financial: i_j is the intangible cost parameter, which accounts for the fact that consumers and firms can attach real or perceived costs to one technology relative to another even though the two might provide the same service at similar financial costs; r

is the private discount rate revealed through empirical research; and v represents variance around technology distribution, reflective of the fact that market conditions differ across the economy and these differences affect the market penetration of a technology even though the technology might be less costly than others when only a single point estimate is used (Figure 1.1). A low value of v means that even technologies with high costs can capture a portion of the new market share. For example, at a value of 1, technology A is able to attain a market share of 40%, even when its lifecycle cost is twice that of technology B. Conversely, if the v parameter takes a high value the least cost technology will dominate the competition. At a value for v of 20, we see that technology A captures almost 100% of the market, as long as its lifecycle cost remains 25% less than the cost of technology B. If technology A costs over 25% more than technology B, technology A fails to penetrate the market.

Figure 1.1: Market heterogeneity in CIMS



LCC = lifecycle costs

Although CIMS' current portrayal of consumers' and firms' decision-making behaviour is an improvement over traditional top-down and bottom-up formulations, the behavioural parameters associated with many technologies currently lack an empirical basis. For the majority of technologies, the discount rate has been derived from literature reviews and expert opinion, and non-financial parameters have been selected to fulfil market share expectations and external forecasts, as well as from meta-analysis (Rivers and Jaccard forthcoming). However, estimating behavioural parameters from these sources limits the ability of CIMS to simulate policy alternatives aimed at influencing technological change. This is because estimates from these sources generally do not differentiate among different types of intangible costs. As a result, model outputs regarding policy costs and environmental outcomes are uncertain.

Recent work at EMRG has focused on addressing this shortcoming by using stated preference data from discrete choice experiments. This research has incorporated conclusions about what influences consumers' and firms' purchasing decisions regarding alternatives in industrial steam generation (Rivers and Jaccard forthcoming), residential heating (Jaccard and Dennis forthcoming), and personal urban transportation (Horne et al. forthcoming). However, the assumption in these studies is that the way in which consumers value technologies and choose among them does not change –that is, the portrayal of consumer preferences is static.[2] As I mentioned previously, preferences can change for a variety of reasons. Therefore, a static representation of preferences in CIMS means that the model might overestimate the social cost of switching to low-GHG

[2] Specifically, the intangible costs (*i* parameter), private discount rate (*r*), and market heterogeneity (*v*) in CIMS do not change during the simulation. A "dynamic" representation of consumer preferences would somehow allow for changes in these parameters during the simulation.

technologies in the long run, especially if we are interested in looking at the adoption of unconventional technologies. By incorporating dynamic consumer preference assumptions, CIMS can simulate these market transformation dynamics.

1.4 Research Questions

My research uses the methodology developed by Rivers, Horne, and Sadler to estimate empirically based behavioural parameters in CIMS, and seeks to extend their work by attempting to capture how long-run preferences can change, as new technologies evolve and gain market share. To meet these goals I developed a methodology to answer the following research questions:

- What are the non-financial costs of adopting hydrogen fuel cell vehicles (HFCVs)?
- Can we expect consumer preferences for HFCVs to change, and if so, on what basis?
- How can we use a hybrid energy economy model (CIMS) to simulate consumer preference dynamics for this vehicle technology?
- What are the likely long-term outcomes of policies aimed at shaping the market for HFCVs in Canada?

My research focuses on eliciting preferences for hydrogen fuel cell vehicles, while manipulating the conditions surrounding the respondents' decision environment in order to trigger changes in these preferences. The hypothesis in this approach is that people's value for hydrogen fuel cell vehicles (and hence, their propensity to choose them over gasoline cars) will change as the number of people owning this vehicle technology increases. I call this phenomenon the "neighbour effect".

I investigate consumer preferences for hydrogen fuel cell vehicles because (1) the widespread adoption of this technology could lead to significant social benefits, and (2) little is known about how its adoption might proceed. We often hear or read about hydrogen fuel cell vehicles in the context of sustainability goals (Ogden et al. 2004). Many call this technology the "car of the future", because of its potential to decrease the pollution arising from vehicle use and to reduce our dependence on fossil fuels. For this product to reach the market, engineers and analysts from different fields must address several technical issues related to the vehicle drive-train itself and the infrastructure required to support the vehicle technology (Azar et al. 2000, Ogden et al. 1999). However, I am not concerned with hydrogen fuel cell vehicle's development pathway; my research concentrates on the conditions required for people to adopt HFCVs.

Some analysts claim that the adoption of HFCVs could require a paradigm shift in the way consumers and producers relate to each other and to the product itself (Bower and Christensen 1995).[3] Hydrogen fuel cell vehicles are a "disruptive" innovation.[4] Disruptive innovations *"[...] shift market structure, represent new technologies, require consumer [and producer] learning and induce behavioural change"* (Mackay 2002). Ayres (2000) adds that, although we know very little about the adoption path of this type of technology in comparison to the evolutionary kind, the potential for profound socio-economic effects from the former is greater.

Theoretical and empirical evidence shows us that people are resistant to change, especially when they are uncertain about the new option (Adamson 2003). Personal

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[3] I use the terms "product" and "technology" interchangeably, although Adamson (2003) clarifies that what consumers buy is a product, typically made up of one or more technologies.
[4] Other terms for "disruptive" are: revolutionary, discontinuous, really new, and radical (Adamson 2003, Schmidt 1998, Freeman 1994).

attitudes towards new technologies play an important role in regards to the adoption potential of HFCVs (Sondermann 2002). Adamson (2003) developed a framework for the adoption of fuel cell vehicles in Europe, concluding that the market penetration of this technology depends on whether manufacturers can meet the needs of three specific consumer groups. My objective is to gain an understanding of the values and preferences of average Canadians when choosing between a conventional gasoline car and a hydrogen fuel cell vehicle. The attitudes and demographics underlying these preferences are less of a focus, but could warrant more attention in future research.

1.4.1 Approach and Structure of the Paper

The general approach involved in this research consisted of:

- Designing an experiment that would allow me to estimate the "neighbour effect" associated with adopting hydrogen fuel cell vehicles;
- Monetizing the intangible (also called non-financial) costs of choosing hydrogen fuel cell vehicles derived from the discrete choice models built from responses to a survey, and assessing the influence of the "neighbour effect" on the intangible costs.
- Using the results from the discrete choice models to set dynamic parameters in CIMS, a hybrid energy-economy simulation model;
- Using the new CIMS configuration to simulate the effects of policies geared at accelerating the market for "disruptive" vehicle technologies in Canada.

The paper begins with a description of the methods I used to implement the first three points of my research approach (Chapter 2). Chapter 3 provides details on the data collection process and includes the results of the survey. Chapter 4 is an analysis of the results pertaining to consumer preference dynamics and their integration into CIMS. This section also includes the results of a series of policy simulation exercises. Finally, Chapter 5 provides a summary and discusses the implications and limitations of this research.

CHAPTER 2 METHODS

2.1 Overview

To answer the research questions I took the following steps. 1) I designed a discrete choice experiment and asked a sample of Canadians to choose between a conventional gasoline vehicle and a hydrogen fuel cell vehicle based on a list of vehicle attributes. 2) To capture the "neighbour effect" I divided the global pool of respondents into four segments, each representing a fictional market share of the disruptive vehicle technology. 3) I used the results of the discrete choice experiment to estimate discrete choice models that quantify the importance of various attributes in decision-making. I also tested for differences among consumer preferences in the four market share groups. 4) I used the discrete choice models to estimate behavioural parameters in a hybrid energy-economy simulation model (CIMS). 5) Based on the differences among the parameter estimates for the discrete choice models and by making assumptions about the input variables I attempted to provide an empirical basis to the function currently being tested to simulate consumer preference dynamics in CIMS.

In the text below I give a more detailed explanation of the methods for each point and the justification behind them.

2.2 Building Discrete Choice Models

2.2.1 Theory

Discrete choice models (DCMs) describe a consumer's decision-making behaviour when faced with a series of competing alternatives, such as technologies, products, or policies (Train 2003). These models assume that, given a choice set, the consumer selects the alternative that they value the most - that is, it provides the greatest utility. DCMs are useful to describe the attributes that contribute to a choice, but they do not describe the decision-making process itself. At an aggregate level, DCMs allow us to assess the probability of market shares of competing technologies by assessing their relative utilities. The utility for technology j, U_j, is defined as:

$$U_j = V_j + \varepsilon_j \qquad \textbf{Equation 2}$$

Where V_j represents the portion of the consumer's utility that the analyst can measure from relating the attributes of the alternatives to the consumer's overall utility. ε_j, represents the factors in consumer choices that the analyst cannot capture in V_j.

V_j or the "measurable utility" is determined by a vector of technological attributes, X_j, each weighted by its corresponding coefficient, β_j. This coefficient is referred to as the taste parameter. Including a constant that is specific to alternative j, captures the average effects on utility this alternative has that are not included in the model. Since we are only interested in comparing relative utilities, given J alternative technologies, one of the alternative specific constants (ASCs) is normalized to zero. By definition, when the model includes ASCs, ε_j has a mean of zero. Thus, the portion of utility for technology j that we can measure takes the form:

$V_j = \beta_j{}^*X_j + ASC_j$ **Equation 3**

To account for the fact that there are certain elements that an external observer to the decision-making process can never fully understand, we can model ε_j as a random variable. In this way, we can use the random variable's joint density distribution to estimate technology market shares probabilistically. We denote the probability that consumers will choose technology *j* over technology *i* as:

$$P_j = Prob\ (U_j > U_i)$$
$$P_j = Prob\ (V_j + \varepsilon_j > V_i + \varepsilon_i) = Prob\ (V_j - V_i > \varepsilon_I - \varepsilon_j)$$
$$\textit{for every } j \neq I$$
Equation 4

2.2.2 Model Assumptions

We cannot estimate a model or calculate the probability of selecting one technology over another without making assumptions about ε_j and V_j. With respect to ε_j, the researcher has to define the term's probability distribution and has to decide whether to allow correlation of this error term across alternatives. Previous studies at EMRG, and the approach taken in this study, have assumed the simplest and most commonly used DCM specification: the multinomial logit model (MNL). The MNL model assumes that the random portion of the utility function is independently and identically distributed across alternatives in the choice set, following a type I extreme value distribution.[5] Integrating the random variable's probability function across all values of ε_i results in the following market share equation:

$$MS_j = \frac{e^{V_j}}{\sum_{k=1}^{K} e^{V_k}}$$
Equation 5

[5] The probability density function of a type I extreme value distribution is similar to the normal distribution, but is right-skewed and assumes a closed form (Morgan and Henrion 1990).

This equation allows us to calculate the probability of selecting technology *j* from a suite of technologies using β coefficients, values for technological attributes (X), and alternative specific constants, if specified. The analyst must have a set of consumer choice observations in order to estimate the β coefficients through a technique called Maximum Likelihood Estimation (MLE). MLE finds the value of β parameters that are most likely, given the actual choices made by the sample under study (Ben-Akiva and Lerman 1985).

The MNL model is the most widely used DCM, largely because its assumptions allow for simple estimation and interpretation of market share forecasts (Zwerina 1997, Train 2003). From the analyst's point of view, the key assumption of independent and identical distribution of the random variable across alternatives is not overly restrictive if we can specify the model in a way that the measurable portion of utility (V_j) sufficiently captures the elements of interest, and the random variable becomes "white noise".

Violations of MNL model assumptions seem to be greater when attempting to predict technology substitution patterns and market shares than when trying to estimate average (and systematic) preference behaviour (Brownstone et al. 2000). One of the goals of my research is to understand aggregate preferences for disruptive vehicle technologies and any dynamics in these. By including the attributes found to most influence decisions on vehicle choices, and by following techniques aimed at improving sample response quality, I have attempted to minimize errors resulting from transgressing MNL assumptions. Ultimately, I had to make trade-offs between the benefits of using a simple model specification and the implications of violating model assumptions. In the rest of this paper, I use U_j to refer to the measurable utility, in order to avoid confusing the V_j with the v parameter in CIMS.

2.2.3 Data Source

We can build discrete choice models from two data sources. Stated preference data result from presenting consumers with a set of hypothetical situations and asking them to decide among two or more alternatives based on a list of attributes. In contrast, revealed preference data represent actual decisions made in the marketplace. Estimating models from either data source has its challenges (Brownstone et al. 2000, Hensher 1999).

Stated preference research has been the preferred approach within EMRG for several reasons (Rivers and Jaccard forthcoming, Horne et al. forthcoming, Jaccard and Dennis forthcoming). 1) Collinearity in revealed preference data can make it difficult to identify the attributes that are significant to decision-making behaviour. 2) We can only observe market behaviour for technologies, products, services, or policies that currently exist. We cannot model demand for new technologies, new attributes, non-market goods and services, or innovative policies using revealed preferences. 3) Collecting revealed preference data can be difficult for at least two reasons. Respondents might find it challenging to recall the attributes that influenced their purchase decisions in the past. Or, in cases where data collection does not involve interviews or surveys, the analyst might need to approach private data banks, subjecting the analyst to costly fees or limiting access to information that might be considered confidential.

Discrete choice experiments designed to elicit stated preferences provide the flexibility to examine a wide range of attributes, customize choice sets faced by each consumer, and include unconventional vehicle technologies and policy options that are currently unavailable. However, stated preference data can include bias, given the hypothetical nature of the survey questions and alternatives, the fact that respondents' actual behaviour and their stated behaviour might differ, and because the respondent might find the survey task overly complex (Train 2003, Fujii and Garling 2003, DeShazo and Fermo 2002, Hensher 1999, Urban et al. 1996). In an attempt to mitigate some of the bias related to task complexity and without compromising efficiencies in data collection, my colleague and I collaboratively developed a web-based survey to gather stated preference data.[6]

2.2.4 Survey Design

The survey design for my research has two major aspects (1) the choice experiment and (2) the treatment of the four market share groups to test for preference dynamics. Details on my approach to testing for the "neighbour effect" are in a separate section to avoid confusion. The choice experiment involved selecting the vehicle attributes and levels that would allow the researcher to estimate, with some degree of confidence, the key influences in consumer choices between a conventional gasoline internal combustion engine vehicle and a hydrogen fuel cell vehicle. As well, I had to decide how many choice situations to give respondents. Several analysts have investigated personal vehicle preferences using discrete choice experiments; I show some of the attributes in these works in Table 2.1.

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[6] Paulus Mau, a graduate student member of EMRG, carried out a companion study focusing on preference dynamics for "evolutionary" vehicle technologies, using hybrid-electric vehicles as a proxy.

Table 2.1: Comparison of attributes selected in this and previous studies

Studies	Attributes				
	Capital cost	Operating costs (including fuel)	Refuelling convenience	Subsidy	Warranty coverage
Brownstone and Train 1999	X	X	X		
Brownstone et al. 2000	X	X	X		
Ewing and Sarigöllü 2000	X	X			
Bunch et al. 1993	X	X	X		
Greene 1997	X		X		
Horne 2003	X	X	X		
This study	X	X	X	X	X

A review of previous studies and consultation with colleagues and experts helped determine the attributes to include in my choice experiment: a) vehicle purchase price (also referred to as capital cost), b) fuel costs, c) the amount of a subsidy the federal government provided as a rebate for purchasing a given vehicle technology, d) warranty coverage, and e) refuelling convenience (i.e., the relative proportion of stations with proper fuel). The rationale for including these attributes is as follows. Purchase price and fuel costs (a and b) were included because most previous studies conclude that they are important criteria when deciding on a vehicle to buy. Also, I would later use the coefficients derived from these attributes to estimate the personal discount rate for the consumer population as a whole. The influence of subsidies could have been incorporated as manipulations of the vehicle purchase prices. Instead, I decided to explicitly include subsidy (c) as an attribute since research in behavioural economics shows that people assess gains with respect to their reference position and not the end-point (Kahneman and Tversky 1984). Following this hypothesis, people might value receiving money to contribute towards their vehicle purchase more than purchasing the vehicle at a discount. Finally, I selected the two non-monetary attributes, refuelling convenience (d) and warranty coverage (e), because they represent conditions that could be affected by policies of government and vehicle manufacturers.

Some important attributes from previous studies that I excluded are: a) relative emissions, b) range, c) power, d) size, and e) storage capacity. I left relative emissions (a) out to minimize respondents' tendency to exaggerate their propensity to choose the more environmentally benign option (as in Urban et al. 1996). I assume that consumers would not have to trade off range (b) and power (c), because engineering studies and technology forecasts indicate that fuel cell vehicles could achieve similar power to conventional gasoline vehicles, and slightly shorter range (Row et al. 2002, Thomas et al. 1998). Size (d) and storage capacity (e) are excluded by some previous studies by asking respondents to imagine that the alternative technology or fuel is available in all vehicle body types (i.e., in all sizes and shapes). This assumption leads to an optimistic portrayal of people's propensity to choose the alternative vehicle technology or fuel. In real markets, the availability of different vehicle body types and vehicle makes are important decision-making criteria, which puts emerging technologies at a competitive disadvantage. My intention was to explicitly include a measure of vehicle make and model availability, but could not find a simple way to represent it.

Next, I selected the number of levels to be presented for each attribute, opting for three levels for most of them. In this way, I would be able to investigate whether people's incremental utility for a given vehicle attribute changes in a non-linear fashion. Greene (1997) reports an example of this in fuel availability. He found that people's marginal utility for increases in the percentage of stations with proper fuel was very different above and below 25%. Table 2.2 shows the possible levels that every attribute could assume in each survey. This configuration yields a 3^6 full factorial design, requiring each respondent to answer 729 choice questions. The design was simplified to a fractional factorial, consisting of eighteen choice questions per respondent. This design was able to accommodate main effects and was well within respondents' cognitive ability (Hensher et al. 2001, Louviere et al. 2000, p. 124).[7]

Table 2.2: Attribute and levels in the discrete choice experiment

	Gasoline Vehicle	Hydrogen Fuel Cell Vehicle (HFCV)
Fuel Cost (weekly or monthly)	• User $_{FC}$ • 110% User $_{FC}$ • 125% User $_{FC}$	• User $_{FC}$
Capital Cost	• User $_{CC}$ • 110% User $_{CC}$ • 120% User $_{CC}$	• 140% User $_{CC}$ • 170% User $_{CC}$ • 190% User $_{CC}$
Stations with Proper Fuel	• All stations	• 1 in 5 • 1 in 10 • 1 in 20
Warranty Coverage	• 5 years or100,000 Km (60,000 miles)	• 5 years or100,000 Km (60,000 miles) • 8 years or 130,000 Km (80,000 miles) • 10 years or 163,000 Km (100,000 miles)
Government Subsidy on Capital Cost (as a rebate)	• No subsidy	• 5% of HFCV purchase price • 10% of HFCV purchase price • 20% of HFCV purchase price

I based the fuel cost and purchase price of the two vehicle types on each respondent's current situation. User$_{FC}$ is the value in dollars that the respondents spend on gasoline on a weekly or monthly basis, and User$_{CC}$ is the price the respondents paid for their current vehicle. Both input variables refer to respondents' primary vehicle,

[7] "Main effects" are the effects of changes in one of the attributes on the dependent variable, which, in this case, is choice (Louviere et al. 2000).

should they own and operate more than one. Variation around gasoline costs reflects possible policy-induced increases in gasoline. Fuel costs for the hydrogen fuel cell vehicle remain constant, following General Motor's assumption that the cost of hydrogen fuel for fuel cell vehicles should be comparable, on a cost-per-driven-distance basis, with that for conventional vehicles.[8] The premiums selected for the purchase price of hydrogen fuel cell vehicles ensured that this vehicle type would always be more costly than its conventional counterpart, corresponding to initial market price expectations for alternative vehicle technologies.[9] Previous studies have found that large differences in purchase price among technology choices can dominate respondents' vehicle choices (Ewing and Sarigöllü 2000). However, when I pilot-tested the levels I initially selected for HFCV's purchase price (110% $User_{CC}$, 125% $User_{CC}$, and 140% $User_{CC}$), respondents consistently chose the hydrogen fuel cell vehicle. So, I adjusted the cost differentials between HFCVs and gasoline cars upwards. I set the proportion of stations with proper fuel for HFCVs using the commercialization scenario in BevilacquaKnight (2001) as a guide, but kept these numbers below 25% of stations with proper fuel. The base warranty coverage (5 years or 100,000 Km) is standard for today. The range in levels for HFCVs illustrates policies that manufacturers might

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[8] http://gm.com/company/gmability/adv_tech/400_fcv/fc_costs.html
Retrieved on August 9, 2003
Ogden et al. (2004) provide analytical evidence in support of this assumption. They argue that fuel costs for fuel cell vehicles per kilometre can be comparable to gasoline costs for conventional vehicles, if corrections for efficiency, infrastructure costs, and fuel production costs are made.
[9] At introduction in 1996, the electric battery version of the Toyota RAV4 sold at twice the value of the conventional RAV4 (Coup 1999). The 2004 manufacturer's suggested retail price (MSRP) for the Honda Civic hybrid electric vehicle was approximately 70% greater than the MSRP corresponding to its gasoline equivalent (retrieved in November 2003 from http://www.honda.ca).

undertake to market unconventional vehicle technologies.[10] Finally, subsidy levels were chosen using current subsidy programmes and tax incentives for alternative vehicles in the United States as references.[11]

2.2.5 Treatment of Market Share Groups

A key innovation of my research is the combination of a choice experiment and the manipulation of the survey sample to test the assumption of changes in preferences for hydrogen fuel cell vehicles as a function of the number of people owning them (the "neighbour effect"). The experimental treatment for the controlled manipulation consisted of using the ratio of hydrogen fuel cell vehicles to conventional gasoline vehicles on the road as a blocking variable ("market share ratio"), and dividing the survey respondents into four segments ("market share groups"), based on the value of this blocking variable. I describe the values I selected for this blocking variable and the way I chose to illustrate each market share ratio to influence respondents' choices in the choice experiment in the following paragraphs.

According to the model in Moore (1999, pp. 11) adoption of innovative technologies occurs in discontinuous steps as different segments of the population are attracted to the new technology. As illustrated in Figure 2.1, the technology adoption curve follows a normal distribution and has five divisions, corresponding to standard deviations. Marketing efforts focus on understanding the profile of people representing each group and the relationship of each group to the next. The goal is to devise targeted

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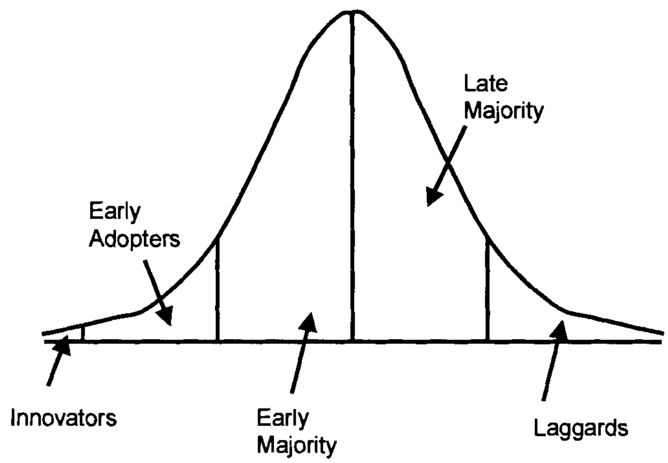
[10] Trace Acres, Director of Corporate Communications at BCAA, confirmed this assumption (personal communication, April 13, 2004).

[11] California's Air Resources Board keeps a searchable database of nation-wide incentive programmes targeting the uptake of alternative vehicles. The database is available at: http://www.driveclean.ca.gov/en/gv/incentives/index.asp

marketing campaigns as adoption proceeds from left to right along the adoption curve until the new technology achieves mainstream market penetration. Experience in the high-tech sector has alerted market researchers to the fact that making the transition from one point to the next along the adoption curve is not a seamless process (Moore 1999, pp. 19). The transition between "early adopters" and the "early majority" is particularly critical, and if left unaddressed can stall the diffusion of the new technology.

Figure 2.1: Technology adoption lifecycle (from Moore 1999)



For this research, I focused on the first three groups of the technology adoption life cycle, represented by four market share groups (two for early adopters). I assumed that hydrogen fuel cell vehicles needed to achieve a 20% penetration rate relative to conventional gasoline vehicles in order to be confident that it will become mainstream in the future. I selected values for the blocking variable based on the number of passenger vehicle sales in Canada in 2002 and the number of hybrid electric-gasoline vehicle sales for that same year. Thus, the first value represents the actual market conditions for hybrid electric-gasoline vehicles and the last value was set to 20% of relative penetration.[12] The two intermediate values represent reasonable midpoints. Table 2.3 shows the values used in the survey.

Table 2.3: Values for the blocking variable

Market Share (MS) Segment	Total Annual Vehicle Sales	Sales Gasoline ICE	Sales New Vehicle Technology
MS1*: Represents "innovators" part of technology adoption curve			
	1,703,511	1,703,063	448
Market share of each technology (percentage of new sales)		99.97	0.03
Market share ratio (new technology: gasoline ICE)			0.03%
MS2: Represents "early adopters" part of technology adoption curve			
	1,703,511	1,620,511	83,000
Market share of each technology (percentage of new sales)		95.13	5.12
Market share ratio (new technology: gasoline ICE)			5%
MS3: Represents early "early majority" part of technology adoption curve			
	1,703,511	1,560,511	143,000
Market share of each technology (percentage of new sales)		91.61	9.16
Market share ratio (new technology: gasoline ICE)			10%
MS4: Represents "early majority" part of technology adoption curve			
	1,703,511	1,454,911	248,600
Market share of each technology (percentage of new sales)		85.41	17.09
Market share ratio (new technology: gasoline ICE)			20%

* Values are based on Canadian data for total passenger vehicle (cars and light duty trucks) sales in Canada and hybrid electric-gasoline vehicle sales in 2002. Source: Automotive News 2003
ICE = internal combustion engine

I used a version of a technique called "information acceleration" to illustrate the blocking variables corresponding to the four market share groups. Marketing experts use this technique in stated preference research to estimate the sales potential of products in the design stage. The advent of user-friendly information technologies has increasingly allowed researchers to experiment with multimedia for this purpose

[12] I used hybrid electric-gasoline vehicle sales for two reasons. Hydrogen fuel cell vehicles are not commercially available yet. However, we (myself and my colleague conducting the companion study) tried to anchor our experiments to actual market conditions so that we would be able to get an indication of real versus stated propensity to choose a new vehicle technology.

(Johnson 1988, Urbany 1986). The goal is to provide the test subjects or respondents with a realistic portrayal of the purchase environment very early in the new product design process, providing insight to producers regarding consumer preferences (Urban and Hauser 1993, pp. 326). Simulating the purchase environment might include an interactive computer interface, which exposes the respondent to a variety of stimuli, such as television advertisements, shopping visits, word-of-mouth experiences, and print advertisements. Because respondents have access to product information at a faster rate than would happen in reality, marketers call the approach "information acceleration" (IA).

Urban et al. (1996) used IA in stated preference research to assess the potential marketability of a battery-electric vehicle developed by General Motors. The similarities between the study by Urban and my own research are straightforward. Both deal with assessing people's preferences for a disruptive vehicle technology, of which they have little to no prior knowledge. Both look at dynamics in preferences, although Urban focuses on dynamics as a function of the information the respondents acquire, whereas mine deals with the "neighbour effect". Both studies use interactive computer media. Therefore, guided by the treatment of Urban et al., I used a scaled-down version of IA to illustrate the blocking variable (market share ratio). I addressed four out of the five aspects of IA as follows.[13] 1) "Future conditioning" and "full information" were addressed collectively by providing respondents two different formats containing similar information on hydrogen fuel cell vehicles with an explicit mention of the number of these vehicles on the road. The technology-specific information included

[13] The fifth aspect, "user experience", was left out of the experiment, given the budgetary limits of this research and the fact that fuel cell vehicle prototypes are not readily available to the public for testing.

references to attributes that are important in decision-making but were left out of the discrete choice experiment. These attributes are: maintenance costs, air emissions, power, safety, reliability, and servicing convenience. Statements or references to these attributes were based on the best available information from manufacturers and technology forecasts. The two formats for each market share group were a one-page fictional magazine article and five fictional accounts of people's experiences with hydrogen fuel cell vehicles. While containing the same technology-specific information among sample groups, the personal accounts differed in their tone and emphasis of diverse aspects of hydrogen fuel cell vehicles, according to the characteristics of different sample segments in the technology adoption lifecycle. For example, respondents who received the treatment depicting market share scenario 1 had access to personal statements from people with the profile shown in Table 2.4 (see Appendix C for profiles corresponding to other points along the technology adoption lifecycle). Positive word-of-mouth statements varied among market share groups, whereas negative statements were generalized for use across all survey treatments.

Table 2.4: Profile for "innovators"

Market Share Scenario 1: Innovators	
Value for blocking variable	Characteristics of reference people
• About 500 hydrogen fuel cell vehicles on the road across Canada • Less than 0.1% MS ratio	• "Innovators" are technology enthusiasts and value a new technology for the sake of it being a new technology. They love HFCVs for their innovative architecture. • They actively seek new products in order to learn about them and test them. Producers or manufacturers trust their evaluations. • They are good critics because they care about the technology. Malfunctions are seen as opportunities for improvement. • If the technology works, they spread this information to potential consumers.
Profile adapted from Moore (1999) and Bolton (1999)	

2) "User control" and "active search" were facilitated by the use of a web-based survey. My colleague and I chose this survey format, as opposed to a mail-out survey, for several reasons, some relating to these aspects of IA. The intention was to make the task interactive and engaging for respondents, without imposing a time constraint. The survey instrument told respondents that they were "required" to read the magazine article and at least two word-of-mouth statements. However, satisfaction of this condition could not be verified. An example of a word-of-mouth statement appears in Figure 2.2.

The complete experimental design took the structure illustrated in Figure 2.3. As previously mentioned, the experiment had two components (1) the information acceleration treatment, and (2) the discrete choice experiment. The IA treatment provided respondents the opportunity to access technical information about hydrogen fuel cell vehicles, and testimonials of fictional users corresponding to hypothetical penetration rates of this technology. The technical information was the same across the four market share groups, whereas the blocking variable and the emphasis of the testimonials differed. Respondents were assigned to the four market share groups at random.

Figure 2.2: Example of "Information Acceleration"

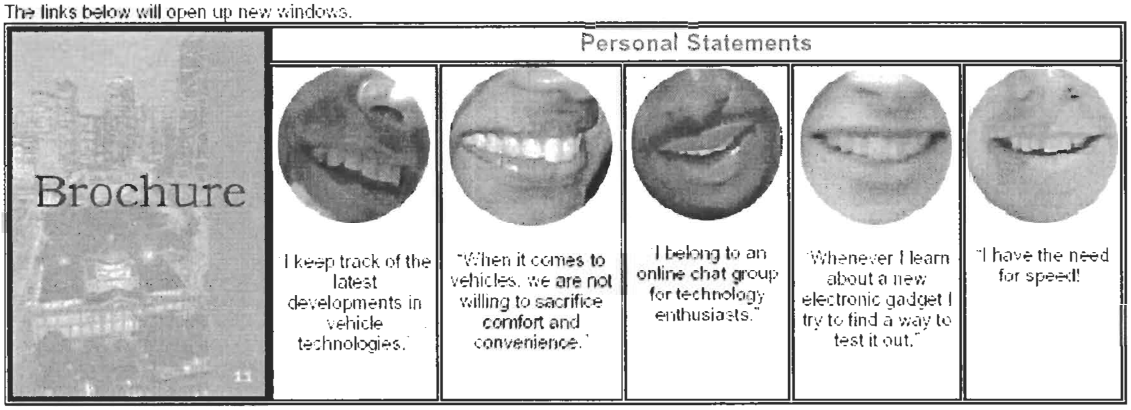
Section 3: Information on Hydrogen Fuel Cell Vehicles

This section illustrates a hypothetical scenario where *500 of the 1.5 million vehicles sold last year were hydrogen fuel cell 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.



I'm Ready!

emrg Urban Transportation Survey

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

When I found out about the hydrogen fuel cell 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. I mean "normal" in terms of performance and handling, but this technology is very far from what we call "normal". Instead of an internal combustion engine, hydrogen fuel cell vehicles are powered by a stack of fuel cells - the vehicle has no engine, no steering column, a lot more passenger space, and no smelly exhaust. Braking and steering are electronic: driving is like flying a plane.

I'm told that you need to fuel up with hydrogen as often as you would with a normal gasoline car. I guess that would be one disadvantage: hydrogen fueling stations are few and far between. But this will change as more people buy this type of vehicle technology. And I'm sure this will happen.

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!

(Close this window to go back to the survey)

Close Window

The discrete choice experiment (DCE) followed the IA treatment. The DCE was identical for all market share groups, and asked respondents to choose between a hydrogen fuel cell vehicle and a gasoline vehicle based on different values of capital cost, fuel cost, refuelling convenience (i.e., proportion of stations with proper fuel), warranty coverage, and government subsidies. The DCE consisted of 18 choice questions. This experimental design would yield four distinct utility functions, corresponding to the four market share groups - as influenced by the IA treatment. The hypothesis was that, as the market share ratio of hydrogen fuel cell vehicles increased, so would the respondents' value for this technology.

Figure 2.3: Experimental design

Information acceleration

Magazine article with information on hydrogen fuel cell vehicles (+ blocking variable). Constants are:

Maintenance costs
Air emissions
Power
Safety
Reliability
Servicing convenience

MS1 (0.03%)	MS2 (5%)[14]	MS3 (10%)	MS4 (20%)
Blocking variable: • 500 HFCVs • Less than 0.1% market share ratio	Blocking variable: • 83,000 HFCVs • 5% market share ratio	Blocking variable: • 143,000 HFCVs • 10% market share ratio	Blocking variable: • 249,000 HFCVs • 20% market share ratio
Word-of-mouth statements: • 3 positive statements from innovators • 2 negative statements	Word-of-mouth statements: • 3 positive statements from early adopters • 2 negative statements	Word-of-mouth statements: • 3 positive statements from early majority • 2 negative statements	Word-of-mouth statements: • 3 positive statements from early majority • 2 negative statements

Discrete choice experiment

18 questions asking respondents to choose between a hydrogen fuel cell vehicle and conventional gasoline vehicle, based on differences in:

Capital cost
Fuel cost
Proportion of stations with proper fuel
Warranty coverage
Subsidies provided by the government

Utility$_{\text{vehicle type at MS1}}$ = βi* (monetary attributes) + βj * (non-monetary attributes) + alternative specific constant	**Utility**$_{\text{vehicle type at MS2}}$ = βi* (monetary attributes) + βj * (non-monetary attributes) + alternative specific constant	**Utility**$_{\text{vehicle type at MS3}}$ = βi* (monetary attributes) + βj * (non-monetary attributes) + alternative specific constant	**Utility**$_{\text{vehicle type at MS4}}$ = βi* (monetary attributes) + βj * (non-monetary attributes) + alternative specific constant

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[14] In the survey version for MS2 two word-of-mouth statements informed respondents that they were "proud of being among the first 8,300 Canadians to own hydrogen fuel cell vehicles". The last part of these statements should have read "among the first 83,000 Canadians". I do not consider this mistake significant because the market share blocking variable was expressed in other ways (5 out of every 100 vehicles sold last year were hydrogen fuel cell vehicles) and respondents would have had the opportunity to digest this information.

Although the focus of the survey was the 18 discrete choice questions, the survey also included questions related to demographics, an exercise related to respondents preferences for makes / models and vehicle body types, questions regarding respondents' attitudes towards the purchase of new technologies, and a question designed to elicit respondents' willingness to pay to keep driving their conventional gasoline vehicle under a new policy regime. Following the approach to conducting surveys and writing the content laid out in Dillman (1999), the survey flowed in this manner:

- Section 1 contained questions about the respondent's current vehicle. The survey web code takes the answers to these questions and customizes other survey questions, including the discrete choice experiments.
- Section 2 aimed at gauging the respondent's level of awareness and knowledge about hydrogen fuel cell vehicles before the experiment. The section also asked respondents to indicate the type of research they engage in prior to buying a car.
- Section 3 consisted of the information acceleration conditioning. The section provided respondents information on hydrogen fuel cell vehicles, including a fictional magazine article on HFCVs and five fictional word-of-mouth statements on this technology, and emphasized the blocking variable (market share ratio).
- Section 4 was the discrete choice experiment containing 18 choice questions. The web code made it possible to randomize the order in which the 18 choice questions appeared for each respondent. This ensured an equal response quality for all 18 questions. The attributes in each choice question were listed at random as well. The objective of this was to prevent respondents from focusing on attributes because of

their position on the list, forcing respondents to pay close attention to each choice question.

- Section 5 had questions relating to people's vehicle preferences, including an exercise designed to gauge respondents' willingness to switch to vehicle makes / models and vehicle body types that are not their preferred ones.
- Section 6 contained questions to gain information on people's attitudes and preferences towards new technologies, including an exercise to place respondents on the technology adoption lifecycle.
- Section 7 had questions pertaining to demographics.

See Appendix BAppendix for a sample of the survey for market share 1 and the information acceleration treatment for all market share groups.

2.3 Integrating DCM Information into CIMS

As already mentioned, researchers at EMRG have developed an approach to converting coefficients estimated from discrete choice models into behavioural parameters in CIMS (Horne et al. forthcoming, Rivers and Jaccard forthcoming, Jaccard and Dennis forthcoming). I used this method to transform the information from the MNL models into behavioural parameters in CIMS. The approach involves balancing the relationship between CIMS' algorithm for estimating market shares of new technologies (Equation 1) and the MNL market share equation (Equation 5). We can calculate the private discount rate ("*r*" in CIMS) and the intangible costs ("*i*" in CIMS) directly from β coefficients derived through MNL model estimation. The private discount rate is based on the relationship between the capital cost coefficient and any coefficients for annual costs. Equation 6 shows this relationship (Train 1985).

$$r = \frac{\beta_{CC}}{\beta_{OC}} \times (1-(1+r)^{-n}) \qquad \textbf{Equation 6}$$

In this equation, β_{CC} is the capital cost coefficient, net of the contribution to utility from government subsidies; β_{OC} is the coefficient for annual operating costs, which only includes fuel costs in this study; and n is the technology lifespan.

To calculate the intangible costs to feed into CIMS we compare each non-monetary β coefficient (including the alternative specific constant or ASC) to the capital cost coefficient and sum all ratios, according to Equation 7.

$$i_j = \sum^{N}\left(\frac{\beta_n}{\beta cc} \times X_n\right) \qquad \textbf{Equation 7}$$

In this equation, i_j is the intangible cost consumers associate with technology j and N is number of non-monetary attributes; β_n is the coefficient for the non-monetary attribute n; X_n is the value for the non-monetary attribute n; and β_{CC} is the coefficient for capital cost.[15] Thus, we calculate i_j, by multiplying the value of each attribute (such as 10% of stations with proper fuel, or unity in the case of the ASC) by the ratio of each non-monetary β coefficient to the capital cost coefficient, and summing all the terms. The analyst has to choose the initial values for X_n. CIMS' current configuration does not allow for changes in X_n values and intangible costs during a run (Horne et al.

[15] We can also annualize the intangible costs by substituting the coefficient for capital cost with the coefficient for annual operating cost in Equation 7.

forthcoming). In the following section I describe the method for changing the intangible costs during a simulation.

We cannot calculate the third behavioural parameter in CIMS, "v", directly from the MNL model coefficients (Rivers and Jaccard forthcoming). Instead, we use the solver function in MS Excel to find a value for v that makes Equation 1 most closely approximate the market share forecast from the MNL model over a range of conditions. Finding the v parameter is an important step in translating the results from DCMs into CIMS, because this factor dictates the relative importance of the explanatory variables in determining the penetration of competing technologies.

2.4 Estimating Preference Dynamics

Aside from the algorithm that allocates new market shares of given technologies during a simulation (Equation 1), two other functions are key to simulating the dynamics of market transformation using CIMS. The first, the "declining capital cost function" (DCC), relates a technology's financial cost to its cumulative production. The function represents "learning-by-doing", accounting for supply-side efficiencies resulting from a doubling of cumulative production. Equation 8 describes the function.

$$C(t) = C(0)\left(\frac{N(t)}{N(0)}\right)^{\log_2(PR)} \qquad \textbf{Equation 8}$$

C(t) is the financial cost of a technology at time *t*; *C(0)* is the initial financial cost of a technology; *N(t)* is the cumulative production of a technology at time *t*; *N(0)* is the production level of a technology during the initial year; and *PR* is the progress ratio. The progress ratio defines the relative cost reduction for each doubling in cumulative production (Rogner 1998). Empirical evidence on the magnitude of this cost reduction exists, with PR values ranging from 0.70 to 0.95 depending on the type of technology and its maturity (McDonald and Schrattenholzer 2001, Dutton and Thomas 1984). A PR of 0.70 indicates a 30% reduction in costs with a doubling in production. Specific to hydrogen fuel cell vehicles, engineering forecasts and lifecycle analyses use progress ratios for fuel cell systems between 0.60 and 0.93 (Ogden et al. 2001, Rogner 1998, Thomas et al. 1998).

The second function, the "declining intangible cost function" (DIC), relates the intangible or non-financial costs of a technology to its market penetration in the previous simulation period. This function accounts for changes in perceptions of new technologies as new information about the technologies' performance becomes available. The assumption is that risk perceptions and resistance to adopting new technologies change as the technologies gain market acceptability (Jaccard et al. forthcoming).[16] Equation 9 describes the dynamics in intangible costs.

$$i(t) = \frac{i(0)}{1 + Ae^{k*MS_{t-1}}}$$ **Equation 9**

In this equation, $i(t)$ is the intangible cost of a given technology at time t; $i(0)$ is the initial intangible cost of a technology; MS_{t-1} is the market share of the technology at

[16] This approach to modelling consumer preferences is, in some ways, similar to agent-based models. The methods I use do not explicitly include a spatial component, which agent-based models do. However, both approaches aim to simulate the dynamics of consumer decision-making based on changes in market conditions, such as the availability of new information and the proportion of neighbours who have adopted the product. For example, Banerjee (1992) developed a model in which agents sequentially make decisions based on previous decisions of other agents. The researcher used this simulation model to understand why people tend to imitate others' actions even when their own information tells them to do something else.

time t-1; and A and k are parameters representing the shape of the curve and the rate of change of the intangible cost in response to increases in the market share of the technology.

One of my research objectives is to estimate the shape of the declining intangible cost function for hydrogen fuel cell vehicles. To do this required the following steps.

1) I calculated the intangible costs associated with hydrogen fuel cell vehicles using the procedure described in Section 2.3. The hypothesis underlying my research is that the experimental treatment will result in four discrete choice models, corresponding to the four technology adoption sample segments, and yielding distinct intangible costs for the non-monetary attributes in the choice experiment (refuelling convenience, warranty coverage, and the constant specific to HFCVs). The expectation is that the change in intangible costs will follow a trend. The intangible costs for a hydrogen fuel cell vehicle estimated from the DCM for the market share group 1 would be higher than those for market share group 2, which would in turn be higher than the intangibles of market share group 3, corresponding to increases in the circulation of hydrogen fuel cell vehicles. Section 4.2 includes a discussion on the validity of these assumptions.

2) I selected reasonable values for the non-monetary attributes that result in changes in intangible costs. Recalling from Section 2.3, monetizing the non-monetary attributes requires weighting each coefficient (with the exception of the alternative specific constant) by an appropriate attribute value. In this way, one can calculate the intangible costs associated with a hydrogen fuel cell vehicle in a world with inadequate fueling infrastructure (e.g., only one out of 20 service stations supply the right fuel). As well, one can calculate the intangible costs for this new vehicle technology as fuel

availability increases and if manufacturers offer extended warranty coverage, for example. In theory, one could assign any value to the two continuous, non-monetary attributes and arrive at intangible costs for a wide range of conditions. However, we do not have any information regarding how the marginal utility for HFCVs changes in response to changes in fuel availability or warranty coverage beyond the ranges in my choice experiment. Even within the ranges in attribute values of the choice experiment, the marginal utility might not change in a linear fashion from data point to data point. For these reasons, I constrain my selection of the series of attribute values to those included in the experiment, further refining the selection based on the results from tests for non-linearities performed on the coefficients of the different DCMs. The results of these analyses appear in Section 3.4.4.

3) I then matched the intangible costs from the DCMs (Equation 7) to the declining intangible cost function (Equation 9). The expectation was that in Equation 9, *i(0)* would be the intangible cost for hydrogen fuel cell vehicles derived from the DCM for market share group 1 (in theory, the market share group with the highest intangible costs). I would then equate the intangible costs calculated from the DCMs for the different market share groups to the costs calculated using the DIC, and I use the solver function in MS Excel to estimate the *A* and *k* parameters that minimize the squared deviation between the two sets of intangible costs. In Section 4.2.1 I describe the procedure in further detail. The *i(0)*, *A*, and *k* enter CIMS as parameters specific to hydrogen fuel cell vehicles, representing the evolution of preference dynamics for this disruptive vehicle technology relative to conventional gasoline vehicles.

The declining capital cost function and the declining intangible cost function provide two mechanisms in CIMS that can combine to simulate market penetration by emerging technologies over the long-term, even if capital costs are prohibitive at the outset of the simulation. I illustrate my extension of CIMS' potential to simulate consumer preference dynamics for hydrogen fuel cell vehicles in Section 4.3. The section includes a series of sensitivity analyses to explore the implications of uncertainty associated with the intangible costs estimated from this research and with the choice of progress ratios for the declining capital cost function.

CHAPTER 3 DATA COLLECTION AND ANALYSIS

3.1 Collecting Data

Once the survey design was complete, I determined the sample size that would allow for robust discrete choice models by running simulations in LIMDEP version 8.0 until I obtained parameters that were statistically significant (to 95% confidence). In this way, I estimated that building multinomial logit (MNL) models for each market share group would require at least 200 completed web-surveys.

To participate in the web-survey Canadians would have to be 19 or over, own a conventional gasoline vehicle (themselves or through immediate family), and commute to work or school at least once a week. The first criterion satisfied Simon Fraser University's requirements for ethical approval and the other two criteria helped capture the actual market participants. Since the survey would be administered via the World Wide Web, respondents also required internet access and an e-mail account.

Participation was also limited to Canadians living in urban centres of a population of roughly 250, 000 and above. The assumption is that accessibility to new vehicle technologies would differ between urban and rural Canadians. The sample was stratified by the following regional groups of urban centres:

- Victoria and Vancouver
- Edmonton, Calgary, Winnipeg and Saskatoon
- Ottawa-Hull, Kitchener, London, St. Catharines-Niagara, Windsor, Toronto, Hamilton and Oshawa
- Montreal and Quebec City
- Halifax and St. John's

The stratification follows that used by Horne (2003), which is meant to increase the likelihood that we would adequately capture preferences from Canadians living in smaller cities. Table 3.1 shows the distribution.

Table 3.1: Desired regional distribution of samples

British Columbia	13%
Prairie provinces	17%
Ontario	38%
Quebec	24%
Atlantic provinces	8%

Synovate, a marketing firm, managed the recruitment process. The initial approach was to draw a random sample from Canadian urban households and to pre-screen potential respondents according to the three participation criteria mentioned above (also see Appendix D). Canadians who met the criteria and agreed to participate in the web-based survey would have to disclose their e-mail address in order to receive the survey link. This approach yielded an unacceptable response rate. It seems that the average Canadian is less apprehensive about disclosing her or his home address than e-mail address. As a result, we turned to the less desirable approach of using Synovate's online panel to fulfil the data requirements.

Synovate's online panel consists of a diverse membership of Canadians representative of all the provinces, official languages, and other socio-demographic variables such as age, income, and education, who periodically participate in surveys and market studies. The recruitment and survey process took place between November 22 and December 2, 2003. Synovate selected four matching samples of approximately 250 respondents each, in accordance with the participation criteria and regional / metropolitan segmentation. On the web survey, they assigned a different hyperlink to each sample group (MS1, MS2, MS3, and MS4). Respondents were recruited to these sample groups randomly.

The panel approach was beneficial in some ways, because it allowed us to achieve the regional distribution listed in Table 3.1 for the four market share groups. However, this approach to recruitment introduces coverage error and self-selection bias into the research.[17] Although it is difficult to generalize about panel members' motivations, people of certain characteristics are more likely to become panel members than others. For example, I observed an overrepresentation of women in our survey samples. Of more direct relevance, self-selecting panel members might have different attitudes towards new technologies than the average Canadian urbanite. In addition, the survey medium itself (the World Wide Web) probably attracted a more technology-accepting panel membership, on the whole, than would a simple random sample of the entire urban population. In Section 3.3.2 I test for these biases by including respondent characteristics as explanatory variables to estimate discrete choice models.

Despite the potential biases of the sampling method and the survey format, the data collection method facilitated reaching a specific response rate and helped minimize measurement error. Specifically on the latter point, I was able to refine the survey questions for clarity, judging from the results of a pilot test. Panel respondents received a version of the survey that was relatively free from ambiguities.

[17] Coverage error results when the sampling frame excludes units in the population (Griffiths et al. 1998, pp. 231).

3.2 Describing the Survey Sample

3.2.1 Sample Characteristics

The entire survey sample that completed the 18 choice questions consisted of 1019 respondents. A minimum of 250 respondents composed each market share group. Ideally, demographic characteristics among market share groups should match closely, so that I am able to attribute possible differences in results to the experimental treatment itself, rather than to confounding factors. Table 3.2 shows that subtle differences in distribution of age, income, and education levels exist among market shares but the differences are not systematic in any way that I detected by simple inspection, and are deemed to be negligible when compared to the characteristics for the entire survey sample (see Appendix E).

Table 3.2: Demographic characteristics by market share group

	MS1 (0.03%) (N_{total} = 250) (N_{demo} = 236)	MS2 (5%) (N_{total} = 252) (N_{demo} = 236)	MS3 (10%) (N_{total} = 258) (N_{demo} = 244)	MS4 (20%) (N_{total} = 259) (N_{demo} = 241)
Age of respondent				
20 or below	0.4	0.0	2.0	1.2
21-25	2.5	4.7	2.5	3.7
26-30	10.2	8.1	11.1	8.7
31-35	13.1	11.0	9.8	10.4
36-40	15.7	14.8	14.3	16.2
41-50	31.8	30.5	26.6	31.1
51-60	17.8	22.9	25.0	23.2
Over 60	8.5	8.1	8.6	5.4
Household income				
$20,000 or less	3.0	3.8	8.2	5.8
$21,000 to $40,000	27.5	23.3	18.9	18.3
$41,000 to $60,000	20.3	25.0	20.9	19.1
$61,000 to $80,000	18.2	22.0	20.9	23.2
$81,000 to $100,000	11.9	8.9	12.3	14.9
$101,000 and above	14.8	14.4	16.0	13.7
No answer	4.2	2.5	2.9	5.0

	MS1 (0.03%) (N_{total} = 250) (N_{demo} = 236)	MS2 (5%) (N_{total} = 252) (N_{demo} = 236)	MS3 (10%) (N_{total} = 258) (N_{demo} = 244)	MS4 (20%) (N_{total} = 259) (N_{demo} = 241)
Region				
Atlantic provinces	7.6	8.9	7.8	8.7
Quebec	23.7	23.3	20.5	24.1
Ontario	36.9	37.7	41.4	35.7
Prairie provinces	15.3	16.9	17.2	19.1
British Columbia	16.5	12.7	12.7	12.4
No answer	0.0	0.4	0.4	0.0
Gender of respondent				
Male	30.5	36.9	34.8	35.7
Female	69.1	63.1	65.2	64.3
No answer	0.4	0.0	0.0	0.0
Education of respondent				
Grade 9 or less	1.3	1.3	0.8	0.4
High school	20.3	30.1	19.7	23.7
College	39.8	35.2	42.2	35.7
University	38.6	33.5	37.3	39.8
No answer	0.0	0.0	0.0	0.4

All values in percentages.

N_{total} = the total number of respondents; N_{demo} = the number of respondents that provided demographic information

Similarly, I compared respondents' characteristics regarding vehicle ownership across market share groups and with the sample as a whole to gauge the representativeness of each market share group. In this way, I confirmed that the distribution of vehicle body types and the number of vehicles owned is fairly constant across the four market share groups, as illustrated in Figure 3.1 and Figure 3.2.

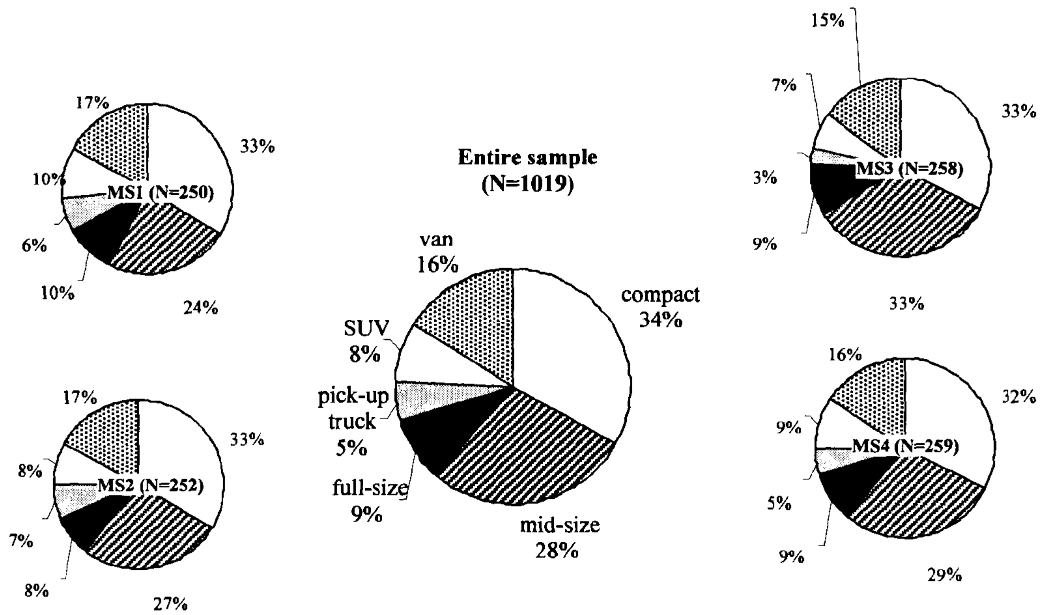


Figure 3.1: Distribution of vehicle body types (respondents' primary vehicle)

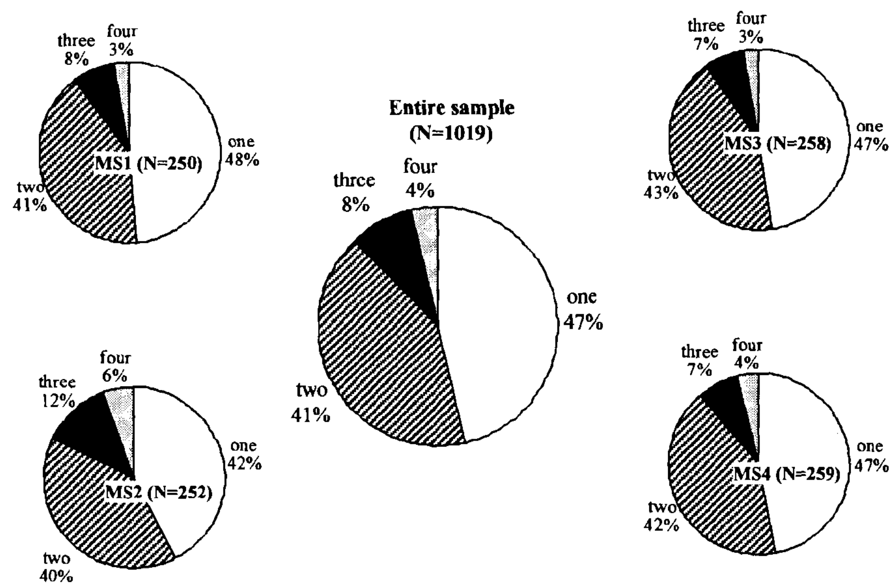


Figure 3.2: Number of vehicles owned by household

Further, people's responses to survey questions specific to hydrogen fuel cell vehicles, key influences in vehicle purchasing decisions, and attitudes towards new technologies were similar across all four market share groups (see Appendix for details). Some of the findings from these questions are:

- Respondents claim to value personal experience most when deciding over what vehicle to purchase, followed by input from dealerships, and word-of-mouth. It was encouraging to see that the latter is an important influence, given my reliance on the "neighbour effect" as a way to capture preference dynamics in the experiment.
- Between 35% and 40% of respondents claim to be unfamiliar with hydrogen fuel cell vehicle technologies, whereas 10% of respondents actively seek information on new developments regarding this technology. In order of importance, respondents are receiving information on hydrogen fuel cell vehicles from radio and television, print media, and word-of-mouth. These findings are consistent among the four market share groups.
- The bulk of respondents (about 80%) fall into the "early majority" portion of the technology adoption lifecycle, about 15% are "laggards", and a minority (about 5%) are "innovators". These proportions are consistent across all market share groups. I based this categorization on respondents' identification with three statements with respect to the adoption of new technologies. Although crude, the exercise was useful to identify whether the survey sample groups had typical attitudes towards the adoption of new technologies.[18] These attitudes would serve as a basis for filtering survey samples for the estimation of discrete choice models.
- About 20% of respondents say that they would not be willing to pay more for a technology solely for its environmental benefits, whereas about 60% say that they would. When asked if they would pay more for an ecologically friendly technology

[18] In this survey question, I used three out of the five categories of technology adoption described in Moore (1999): innovators, early majority, and laggards. I did this to simplify the response task, while giving us some insight into the distribution of attitudes among the two extremes and a mainstream measure.

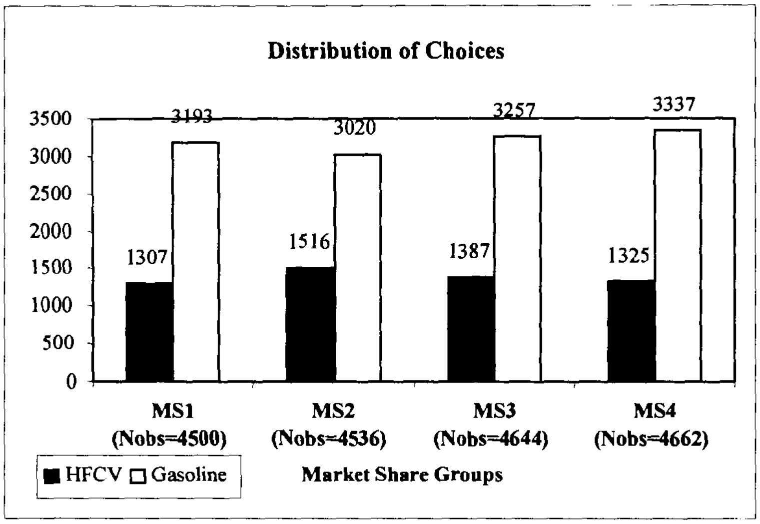
that provided some personal benefit, about 75% of people said they would, whereas about 10% said they would not.

3.3 Estimating Discrete Choice Models

3.3.1 Assessment of Choices

Section 4 of the survey consisted of the discrete choice experiment composed of 18 vehicle choice questions. The total number was 18,342 vehicle choices ([1019 respondents] X [18 questions]). The numbers of observations per market share group were: 4,500 (MS1), 4,536 (MS2), 4,644 (MS3), and 4,662 (MS4). Estimating multinomial logit (MNL) models requires that respondents choose both the hydrogen fuel cell vehicle and the conventional gasoline vehicle in a pattern that allows us to capture the vehicle attributes' contribution to utility. Respondents preferred gasoline vehicles in over 50% of the choice situations, but they selected hydrogen fuel cell vehicles enough times to be able to estimate discrete choice models. Figure 3.3 shows the number of times respondents chose each vehicle technology, also illustrating that the choice distribution across the four market share groups is similar.

Figure 3.3: Frequency of vehicle technology chosen



(N_{obs} = number of observations)

Figure 3.4 allows us to further assess the variability of respondents' choices among market share groups. The graph shows the frequency with which market share groups chose HFCVs on the y-axis, and the choice sets on the x-axis.[19] Several studies document the importance of assessing whether stated preferences change during repeated and sequential measurement (DeSarbo et al. 2004). In my experiment, the sequence of choice questions was randomized anew for each respondent. Thus, the similarities in certain choices among market share groups and the clustering of stronger differences for choices 6 through 13 shown in Figure 3.4 are not an artefact of the questions' sequencing. The pattern reflects respondents' preferences.

[19] A "choice set" is a particular combination of attributes for hydrogen fuel cell vehicles and gasoline vehicles, the values of which are determined by the experimental design. In this research, the choice experiment consisted of 18 choice sets or questions.

Figure 3.4: Variability in respondents' choices

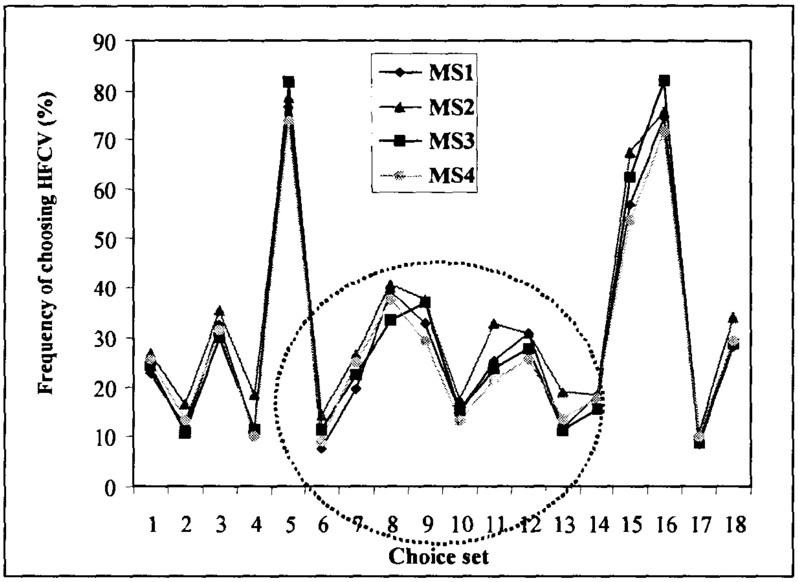
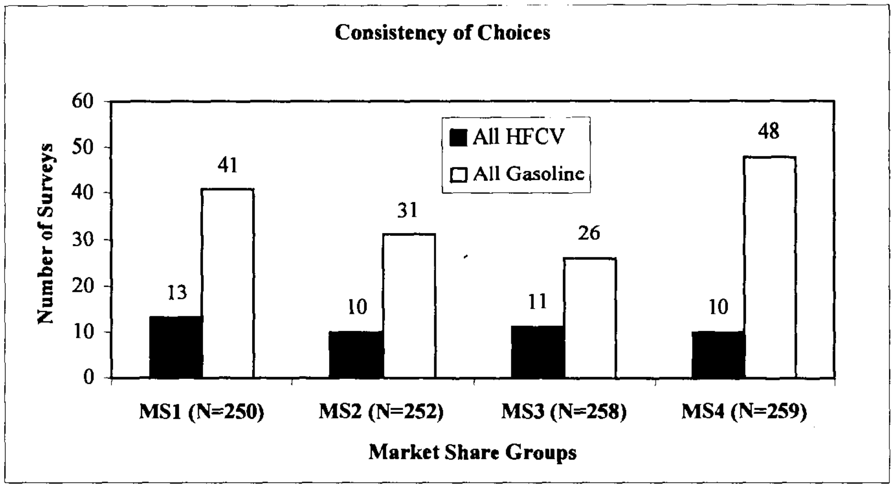


Figure 3.5 shows the number of surveys in which the respondents chose the same vehicle technology in all 18 questions. This result is important to assess, because if respondents frequently choose one technology over the other in all choice situations, the alternative specific constant can dominate the utility calculation. In my study, respondents chose the same vehicle type in all 18 questions from 14 to 22% of the time, depending on the market share group. These frequencies are lower than those in a vehicle choice study by Horne (2003).

Figure 3.5: Frequency of choosing the same alternative across all choice sets



Horne's interpretation of uniformity in vehicle choices by a single respondent was that people considered each question independently but selected the vehicle type based on an attribute not included in the choice experiment. I agree with his explanation, and in a later section I discuss the relative contribution of the alternative specific constant to respondents' aggregate utility for the two vehicle technologies in my research.

3.3.2 Multinomial Logit Models

As mentioned in Section 2.2.2, I estimated multinomial logit (MNL) models yielding the most likely β parameters given the data set and the utility formulation. I used LIMDEP version 8.0 to find the maximum likelihood estimates (MLE) for each MNL model. The experimental design accommodated a range of ways of representing the utility formulation, which means that different MNL models can be estimated, depending on the explanatory variables one includes.

1) Basic Model: One can estimate a "basic" MNL model for each market share group (MS1, MS2, MS3, and MS4) using vehicle attributes only. In this case, the utility for conventional gasoline vehicles and hydrogen fuel cell vehicles for each market share group results from using Equation 10:

$$U = \beta_{CC} \cdot CC + \beta_{FC} \cdot FC + \beta_{RC} \cdot RC + \beta_{SUB} \cdot SUB + \beta_{W} \cdot W + \beta_{HASC} \qquad \textbf{Equation 10}$$

Where *CC* is the capital cost; *FC* is the weekly fuel cost; *RC* is refuelling convenience, which is the proportion of stations with proper fuel; *SUB* is government subsidy; *W* is warranty coverage; and *HASC* is the constant specific to hydrogen fuel cell vehicles.[20] Except for the alternative specific constant, all the β coefficients have the same effect on utility regardless of the vehicle technology. This model specification and the three below treat all attributes as continuous variables, resulting in linear β coefficients.

2) Basic Model with Respondent Characteristics: one can respecify the basic model to include socio-economic characteristics and attitudes of respondents as explanatory variables, in order to test whether personal characteristics influence people's responses to vehicle technologies (Ewing and Sarigollo 1998). We do this by incorporating interaction terms between respondent characteristics and the alternative specific constant, where respondent characteristics are treated as "dummy variables" (i.e., either "1" or "0", depending on whether the respondent has this characteristic or does not). Specifically, I tested the following respondent characteristics: income group (*Y*), home region (*REG*), respondents' stated willingness to pay a premium for ecologically-friendly products (*ECO*), respondents' stated willingness to pay a premium

[20] Since we are only interested in the relative difference between the two vehicle technologies, the alternative specific constant for conventional gasoline vehicles is set to zero in all cases.

for ecologically-friendly products contingent on their provision of personal benefit (*OWN*), and whether the respondent was categorized as an innovator, laggard, or early majority (*ADOPT*). The resulting utility equation for hydrogen fuel cell vehicles for each market share group would look like:

$$U_{HFCV} = \beta_{CC} \cdot CC + \beta_{FC} \cdot FC + \beta_{RC} \cdot RC + \beta_{SUB} \cdot SUB + \beta_{W} \cdot W + \beta_{HASC} + \sum \beta_{HASC} \cdot (Y, REG, ECO, OWN, ADOPT) \qquad \textbf{Equation 11}$$

Since we set the alternative specific constant associated with gasoline vehicles to zero, contributions to utility as a result of personal characteristics are only assessed relative to hydrogen fuel cell vehicles. Thus, the utility function for gasoline vehicles would have the same form as Equation 10 but β coefficients (and, hence, utility) would be different.

3) Chow Test Model: instead of estimating a separate MNL model for each market share group, one can also pool the data sets and estimate one model using a test proposed by Chow (1960). The test is a type of piecewise regression to estimate β coefficients of subsections of the sample, in which the delineation of subsections are known and defined *a priori*. In this case, we consider β coefficients for MS1 as the base level coefficients. The contribution to utility from the other market share groups enter the utility formulation as dummy variables, which interact with the generic vehicle attributes. The utility equations for conventional gasoline vehicles and hydrogen fuel cell vehicles for the four market share groups are below. As before, the alternative specific constant only applies to hydrogen fuel cell vehicles.

$$U_{MS1} = \beta_{CC} \cdot CC + \beta_{FC} \cdot FC + \beta_{RC} \cdot RC + \beta_{SUB} \cdot SUB + \beta_{W} \cdot W + \beta_{HASC}$$ **Equation 12**

$$U_{MS2} = U_{MS1} + \beta_{MS2CC} \cdot CC + \beta_{MS2FC} \cdot FC + \beta_{MS2RC} \cdot RC + \beta_{MS2SUB} \cdot SUB + \beta_{MS2W} \cdot W$$ **Equation 13**

$$U_{MS3} = U_{MS1} + \beta_{MS3CC} \cdot CC + \beta_{MS3FC} \cdot FC + \beta_{MS3RC} \cdot RC + \beta_{MS3SUB} \cdot SUB + \beta_{MS3W} \cdot W$$ **Equation 14**

$$U_{MS4} = U_{MS1} + \beta_{MS4CC} \cdot CC + \beta_{MS4FC} \cdot FC + \beta_{MS4RC} \cdot RC + \beta_{MS4UB} \cdot SUB + \beta_{MS4W} \cdot W$$ **Equation 15**

β_{MS2CC}, for example, is the coefficient for the interaction term between the market share variable for MS2 and the contribution to utility from vehicle capital cost. If the coefficient is statistically significant at a certain level, then we add its value to that of the base model coefficient (in other words, when it comes to capital cost, there is value in knowing that 5% of Canadians drive a HFCV).

4) Chow Test Model with Respondent Characteristics: this specification includes socio-economic and personal attitudes as explanatory variables, in the same way as the "Basic Model with Respondent Characteristics" but also includes gender (*F*) and age class (*AGE*). For example, the resulting utility equation for hydrogen fuel cell vehicles for MS2 is:

$$U_{HFCV \cdot MS2} = \beta_{CC} \cdot CC + \beta_{FC} \cdot FC + \beta_{RC} \cdot RC + \beta_{SUB} \cdot SUB + \beta_{W} \cdot W + \beta_{HASC} + \beta_{MS2CC} \cdot CC + \beta_{MS2FC} \cdot FC + \beta_{MS2RC} \cdot RC + \beta_{MS2SUB} \cdot SUB + \beta_{MS2W} \cdot W + \sum \beta_{HASC} \cdot (Y, REG, F, AGE, ECO, OWN, ADOPT)$$ **Equation 16**

In this paper, I focus on the results from the "Basic Model" for the following reasons. 1) This model specification is simple and allows for independent manipulation of parameters for different market share groups. 2) Model specifications that included personal characteristics exhibited collinearities among income, age class, and home region. 3) Aside from a regional sector representation CIMS does not accommodate personal attributes, which means that integrating parameter estimates from MNL models with personal characteristics would not be a useful exercise.

Regardless of CIMS' data needs, alternative MNL model specifications provide valuable information in their outputs. In particular, some studies on the adoption of new technologies suggest that introducing attitudes or values as explanatory variables into models with demographics, monetary variables, and technology-specific attributes improves models' explanatory power (Arkesteijn and Oerlemans 2005, Mourato et al. 2004, Sondermann 2002). Sondermann (2002), for example, found that 59% of the variation in consumer acceptance of HFCVs was explained by attitude towards air pollution, attitude towards HFCVs, personal involvement in reducing air pollution, and perceived usefulness of a HFCV. Below is a summary of results from model specifications on my study data other than the "Basic Model" (see Appendix E for detailed results). This summary only presents information that the "Basic Model" does not provide.

1) Basic Models with Respondent Characteristics: collinearities between home region and income precluded the estimation of models containing both variables. Therefore, I estimated two models for each market share group, with the only difference being the inclusion of home region or income. Three findings stand out from comparing the results across all market share groups. All results I mention are based on the statistical significance of coefficients at the 95% level. First, the models including income

as an explanatory variable are a better fit for the data than the models with home region. Unexpectedly, income has a negative effect on utility for hydrogen fuel cell vehicles. The magnitude of the income effect on the propensity to choose HFCVs is at least as important as fuel cost (as indicated by t-ratios). Second, in both types of models stated willingness to pay a premium for ecologically-friendly products increases the likelihood of choosing a HFCV. The magnitude of the effect varies among market share groups, positively contributing to utility for HFCVs as much as the alternative specific constant or as little as fuel cost. Third, respondents' stated attitude towards new technologies (innovator, laggard, or early majority) has an impact on utility for HFCVs. The magnitude and direction of the impact vary among market share groups, but the contribution to utility is comparable to that of some vehicle attributes.

2) Chow Test Model: this model specification results in similar market share predictions as those from the "Basic Models". The value of the Chow Test Model is that it allows us to verify that there are differences in utility for HFCVs among the market share groups. Specifically, market share group 2 (MS2) values capital cost and refuelling convenience differently than the baseline (MS1), and MS3 values capital cost and government subsidy differently than the baseline.

3) Chow Test Model with Respondent Characteristics: regarding personal characteristics and attitudes, this model specification produces results comparable to the "Basic Models with Respondent Characteristics". Gender (which I did not include in the "Basic Models with Respondent Characteristics") does not affect the likelihood of choosing a HFCV, which means that the overrepresentation of women in the survey sample does not bias the results. Differences in the valuation of vehicle attributes

between the model that includes home region and the income model are relatively small. The former mimics the results for the "Chow Test Model". In the income model we see an additional statistically significant component: MS4 values capital cost and fuel cost differently than the baseline. The increase in both vehicle attributes contributes positively to utility, a result that is difficult to explain.

The results from models that include respondent characteristics alert us to the fact that stated attitudes can help explain the propensity for choosing HFCVs over gasoline vehicles. I did not consider stated attitudes when designing the choice experiment or recruiting respondents. One way to remove attitudinal bias in favour or against HFCVs from the market share groups is to filter out the innovators and laggards from the four data sets. I consider this approach necessary in order to be able to capture changes in the intangible costs of Canadian urbanites with mainstream attitudes about new technologies. Although the application of this filter reduces the number of observations per group, it improves the explanatory power of the four "Basic Models" and it may provide a better portrayal of the average Canadian's preferences for disruptive vehicle technologies. I elected to estimate separate MNL models for the early majority in each of the four market share groups. From this point on I refer to early majority models as "majority", given the broad categorization into three technology adoption groups. I also estimated a single model for all laggards, aggregated from all market share groups, and I did the same for the innovators. The next section provides a detailed look at the results from the "Basic Models".

3.4 Analyzing the Results from the Basic Models

Table 3.3 shows the MNL model results from the majority category of respondents in each of the four market share groups, including the MLE coefficients (β), and an indication of their statistical significance (t-ratios). The four market share groups correspond to different degrees of fictional market penetration of HFCVs relative to gasoline vehicles. For market share group 1 (MS1), market penetration of HFCVs is assumed to be 0.03%; MS2 assumes a penetration of 5%, MS3 of 10%, and MS4 of 20%. Results from the models for innovators and laggards, each a single group aggregated from all market share groups, are in Table 3.4. To test the models' explanatory power, we compare the log-likelihood of the full model to (1) the log-likelihood function of a model without coefficients, and (2) to the log-likelihood of a model with alternative specific constants (ASC) only. These test statistics for each of the six MNL models appear in italics, in the two last rows of Table 3.3 and Table 3.4. They indicate that each of the six models, as specified, explain the data better than models without coefficients or with alternative specific constants only with 99.9% confidence.

Table 3.3: Best fit statistics for "Basic Models" (majority)

Attribute	MS1 model (0.03%)		MS2 model (5%)		MS3 model (10%)		MS4 model (20%)	
	ß	t-ratio	ß	t-ratio	ß	t-ratio	ß	t-ratio
Capital cost	-1.84E-04	-18.71	-1.95E-04	-20.22	-1.96E-04	-19.98	-1.39E-04	-17.13
Fuel cost	-3.47E-02	-3.21	-9.36E-03	-1.11**	-3.18E-02	-3.83	-2.64E-02	-2.84
Government subsidy	3.15E-04	10.07	2.75E-04	8.74	3.65E-04	11.61	2.70E-04	9.79
Refuelling convenience	9.69	14.15	9.53	14.60	9.89	14.73	9.01	14.18
Warranty coverage	1.56E-01	7.36	1.09E-01	5.60	1.71E-01	8.20	1.53E-01	7.77
ASC - Hydrogen fuel cell vehicle	8.10	13.21	8.58	14.56	8.13	13.56	7.28	12.88
Observations	3,348		3,492		3,672		3,636	
Log likelihood - *full model (F)*	-1,653.57		-1,842.09		-1,733.71		-1,893.01	
Log likelihood - *constants only (ASC)*	-2,056.56		-2,275.26		-2,193.96		-2,239.59	
Log likelihood - *no coefficients (0)*	-2,320.65		-2,420.47		-2,545.24		-2,520.28	
-2(L(F) - L(0))*	*1,334.18*		*1,156.76*		*1,623.05*		*1,254.55*	
-2(L(F) - L(ASC))*	*806.00*		*866.34*		*920.50*		*693.17*	
All coefficients are significant at the 95% confidence level with the exception of fuel cost for MS2 (**).								

Table 3.4: Best fit statistics for "Basic Models" (innovators and laggards)

Attribute	Innovators		Laggards	
	ß	t-ratio	ß	t-ratio
Vehicle capital cost	-8.84E-05	-6.60	-1.20E-04	-9.61
Fuel cost	8.39E-03	0.74**	7.81E-04	0.06**
Government subsidy	3.37E-04	6.43	2.33E-04	6.12
Refuelling convenience	6.210	5.08	6.70	7.85
Warranty coverage	8.24E-02	2.23	1.35E-01	4.95
ASC - Hydrogen fuel cell vehicle	5.04	4.63	4.72	6.26
Number of observations	810		2,286	
Log likelihood - *full model (F)*	-497.17		-1,070.29	
Log likelihood - *constants only (ASC)*	-543.90		-1,186.64	
Log likelihood - *no coefficients (0)*	-561.45		-1,584.53	
-2(L(F) - L(0))*	*128.56*		*1,028.48*	
-2(L(F) - L(ASC))*	*93.46*		*232.70*	
All coefficients are significant at the 95% confidence level with the exception of fuel cost (**).				

All coefficients contribute significantly to the fit of each model at a 95% confidence level with the exception of fuel cost for (1) the 20% market share group (MS4 model) of the majority and (2) the models for innovators and laggards. The t-ratios for fuel costs indicate that the relative contribution to utility from this attribute is the lowest in comparison to the remaining attributes. Capital cost, refuelling convenience, and unknown attributes specific to HFCVs not included in the experiment (as indicated by the ASC) are the greatest determinants of utility for the four majority market share groups and for laggards. For innovators, capital cost and government subsidy are the most important attributes in choosing a vehicle, followed by refuelling convenience. All coefficients have the expected directions of influence across the six models: increasing capital cost and fuel cost decreases utility (fuel cost is not significant in the models for innovators or laggards), whereas increasing government subsidies, refuelling convenience (i.e., the proportion of stations with proper fuel), and warranty coverage increases utility. As hypothesized during the survey design stage, marginal changes in government subsidy influence utility disproportionately in comparison to changes in capital costs. All four majority models and the one laggards model value a one-dollar increase in government subsidy about twice as much as a dollar decrease in capital cost. Innovators value a one-dollar increase in subsidies almost four times as much as a one-dollar decrease in capital cost. All else being equal, respondents in all groups value hydrogen fuel cell vehicles (HFCV) more than conventional gasoline vehicles, as indicated by the high value of the ASC. This is a common finding in vehicle choice studies: non-gasoline vehicles seem to have an intrinsic value that makes them more attractive than gasoline vehicles *ceteris paribus* (Horne et al. forthcoming, Ewing and Sarigöllü 2000, and Brownstone et al. 2000).

3.4.1 The Scale of the Models

Recall from Section 2.2.2, in a "good" MNL model specification the random variable (or error term) has limited bearing on market share forecasts because the scale of model is large in relation to the error. In other words, market share forecasts depend on the magnitude of attribute values and alternative specific constants ("measurable" or "observed" utility). To assess the relative scale of my models, that is the proportion of utility I have captured with the attributes relative to the error term, I made comparisons with previous vehicle choice studies. I took the commonly specified coefficients for capital cost and refuelling convenience as points of comparison. An assessment of the type shown in Table 3.5 only gives us a relative measure of a model's scale; it assumes that capital costs and the measure of fuel availability affect respondents' choices in the same way across all model specifications. The coefficients for capital cost range from 2.26 times (Ewing and Sarigöllü 2000) greater to 0.46 times less (Horne et al. forthcoming) than the coefficients for my models. The coefficients for refuelling convenience from other studies range in magnitude from 0.12 (Horne et al. forthcoming) to 0.48 (Bunch et al. 1993) times the coefficients of this study. Judging from these figures we can say that the scales of the models in this study are within ranges of previous studies. The attributes and alternative specific constants in this study have a plausible influence on market share forecasts.

Table 3.5: Comparison of selected attributes

Study	Value of capital cost coefficients relative to those in this study					
	Innovators	MS1 (0.03%)	MS2 (5%)	MS3 (10%)	MS4 (20%)	Laggards
Ewing and Sarigöllü 2000	2.26	1.09	1.03	1.02	1.44	1.67
Bunch et al. 1993	1.52	0.73	0.69	0.68	0.96	1.12
Horne et al. forthcoming	1.02	0.49	0.46	0.46	0.65	0.75
Study	**Value of refuelling convenience coefficients relative to those in this study**					
	Innovators	**MS1 (0.03%)**	**MS2 (5%)**	**MS3 (10%)**	**MS4 (20%)**	**Laggards**
Bunch et al. 1993	0.48	0.31	0.31	0.30	0.33	0.44
Horne et al. forthcoming	0.19	0.12	0.12	0.12	0.13	0.17

To further illustrate the capacity of the six models to generate a wide range of outputs (market shares from 0% to 100%), I used two extreme scenarios, in which vehicle attributes took on values that would result in low utility ("worst case") and high utility ("best case"). I estimated market share forecasts for gasoline and hydrogen fuel cell vehicles for the models based on both sets of attribute values. Table 3.6 lists the attribute values and

Table 3.7 shows that the models allow both types of vehicle technologies to capture a wide range of market shares, although gasoline vehicles cannot reach 100% penetration.

Table 3.6: "Best" and "worst" case values for vehicle attributes

Attribute	Best case	Worst case
Vehicle capital cost ($)	17,100	35,000
Fuel cost ($ / week)	20	80
Government subsidy ($)	2,500	0
Refueling convenience	100%	5%
Warranty coverage (years)	10	5

Table 3.7: Market penetration under "worst" and "best" cases

Model	*P(Gas)*		*P(HFCV)*	
	Best case	Worst case	Best case	Worst case
Innovators	96.07%	0.00%	100.00%	3.93%
Majority MS1	99.97%	0.00%	100.00%	0.03%
Majority MS2	99.68%	0.00%	100.00%	0.32%
Majority MS3	99.98%	0.00%	100.00%	0.02%
Majority MS4	99.89%	0.00%	100.00%	0.11%
Laggards	99.32%	0.00%	100.00%	0.68%
P(Gas) = probability of choosing conventional gasoline vehicle; P(HFCV) = probability of choosing hydrogen fuel cell vehicle				

Horne (2003) found similar capacity and limitations in his vehicle choice model for four vehicle types. He noted that the high value of alternative specific constants prevented three out of the four vehicle types to achieve 100% market penetration, which is a similar situation for gasoline vehicles in my study.

3.4.2 Dominance of Alternative Specific Constants

Table 3.3 and Table 3.4 show that both the magnitude of the alternative specific constant for hydrogen fuel cell vehicle and its contribution to utility (as indicated by the t-ratios) in the six models of my study are high. This means that hydrogen fuel cell vehicles can achieve significant market shares just by virtue of being hydrogen fuel cell vehicles, all else being equal. The dominance of the alternative specific constant over utility is illustrated in two cases, one in which all vehicle attributes assume the same values regardless of vehicle technology and the other in which the only difference is the relative proportion of stations with proper fuel (Table 3.8 and Table 3.9).

Table 3.8: Market share forecasts with equal attribute values

Attribute	Gas	HFCV
Vehicle capital cost ($)	17,100	17,100
Fuel cost ($ / week)	23	23
Government subsidy ($)	0	0
Refueling convenience	100.00%	100.00%
Warranty coverage (years)	5	5
Is it HFCV? (1=yes, 0=no)	0	1

Model	*P*(Gas)	*P*(HFCV)
Innovators	0.64%	99.36%
Majority MS1	0.03%	99.97%
Majority MS2	0.02%	99.98%
Majority MS3	0.03%	99.97%
Majority MS4	0.07%	99.93%
Laggards	0.88%	99.12%

Table 3.9: Market share forecasts with different values for refuelling convenience

Attribute	Gas	HFCV
Vehicle capital cost ($)	17,100	17,100
Fuel cost ($ / week)	23	23
Government subsidy ($)	0	0
Refueling convenience	100.00%	0%
Warranty coverage (years)	5	5
Is it HFCV? (1=yes, 0=no)	0	1

Model	*P*(Gas)	*P*(HFCV)
Innovators	76.38%	23.62%
Majority MS1	83.15%	16.85%
Majority MS2	72.19%	27.81%
Majority MS3	85.34%	14.66%
Majority MS4	84.91%	15.09%
Laggards	87.86%	12.14%

Table 3.8 shows that under equal conditions, respondents' propensity to choose hydrogen fuel cell vehicles over gasoline vehicles is overwhelming. Gasoline cars do not even capture one per cent of the market share. Of course, an equalization of all attributes and conditions would probably require radical policy changes to "even the playing field". In any case, there will always be a population segment willing to pay for familiar, comfortable technologies but even the model for laggards indicates a marked preference for the new vehicle technology. This finding differs from Mau's (unpublished manuscript) companion study on consumer preferences for hybrid electric vehicles (HEVs). His models indicate that people value gasoline vehicles more than HEVs, all else being equal. But the value for gasoline vehicles decreases as a function of market share groups. Although it is encouraging to see the potential market impact of hydrogen fuel cell vehicles forecasted by the models in my study, Table 3.9 provides

reason to take this optimistic result with caution. The basic models predict that even in the absence of stations with the proper fuel for HFCVs, the technology could capture between 12 to 28% of gasoline vehicle's market share!

Since hydrogen fuel cell vehicles are not commercially available I am not able to validate the model predictions to observed market conditions. However, results from the companion HEV are able to draw on actual market data. Table 3.10 shows the results predicted by the basic HEV model using realistic attribute values (Mau, unpublished manuscript). The model prediction exceeds the actual market ratio in 2002 by about 17%. In the discrete choice experiment, we told respondents to select the vehicle they would most likely choose as their next vehicle purchase. Therefore, we cannot rule out the lag in capital stock turnover as a possible explanation of the disparity between revealed market conditions and stated intent. For example, if 17% of respondents say that their next vehicle will be an HEV, but on average respondents own vehicles for 8 years, then only about 2% would buy an HEV next year, assuming an equal distribution of vehicle vintages.[21] I discuss other possible reasons below.

[21] The average vehicle ownership is based on results from my research. However, these numbers are likely to match the results from the companion study on HEVs.

Table 3.10: Predicted versus actual penetration of hybrid electric vehicles (from Mau, unpublished manuscript)

Attribute	Gas (Honda Civic)	HEV (Honda Civic Hybrid)
Vehicle capital cost	$17,100	$29,510
Fuel cost (per week)	$23	$13.30
Government subsidy	$0	$0
Cruising range (days)	11	19
Warranty coverage (years)	5	5
Is it gasoline? (1=yes, 0=no)	1	0

	P(Gas)	*P*(HEV)
MS1	83%	*17%*

*MS1 represents a scenario in which the market share ratio between HEV and gasoline vehicles is **0.03%** - reflective of the Canadian market in 2002.*

P(Gas) = probability of choosing conventional gasoline vehicle; P(HEV) = probability of choosing hybrid electric-gasoline vehicle

The model predictions for HEVs and HFCVs obviously include much uncertainty, but it is clear that respondents are attracted to both hybrid electric and hydrogen fuel cell vehicles for reasons that cannot be fully explained by our basic model specifications. However, the influence of the alternative specific constant for the new vehicle technology to dominate market share forecasts is unique to the hydrogen fuel cell study. Several factors could account for HFCV's dominant appeal; I suggest that these three are important: 1) respondents overstating their preference for HFCVs because of a perceived "social good" aspect; 2) attributes omitted from the discrete choice experiment important in decision-making; and 3) respondents' reaction to disruptive technologies.

Researchers assessing the marketability of environmentally friendly technologies or products often find a discrepancy between respondents' stated attitudes towards an environmental or social outcome they perceive as desirable (such as improving air quality) and their revealed behaviour (buying fuel inefficient vehicles and neglecting alternative modes of transport) (Roberts and Bacon 1997). Sagoff (1988) offers the explanation that people's preferences vary according to whether, at the moment of observation, they perceive their decision to affect their personal utility or society at large. During the information acceleration (IA) portion of the survey, respondents received information on the low emissions of hydrogen fuel cell vehicles in comparison with gasoline vehicles. In this way, the information provided to respondents on HFCVs might have placed gasoline vehicles at a competitive disadvantage given that there was no mention of advances in conventional gasoline vehicles that could result in substantial fuel efficiencies.[22] Thus, the information might have had a strong effect on respondents' frames of mind during the survey, putting the public social / environmental good in the forefront, though only temporarily. In fact, the "basic models with respondent characteristics" and "Chow test models with respondent characteristics" (Section 3.3.2) indicate that the interaction term between respondents' stated willingness to pay a premium for a technology that is ecologically friendly and the alternative specific constant for HFCVs is statistically significant and positive, which means that the stated attitude increases the likelihood of choosing HFCVs.

A second possible explanation has to do with attributes that I did not include in the choice experiment. The IA part of the survey gave general statements pertaining to maintenance costs, power, safety, reliability, and servicing convenience of hydrogen fuel cell vehicles. The intent was to give respondents the sense that hydrogen fuel cell

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[22] Engineering studies indicate that load reduction technologies and power train improvements could make gasoline internal combustion engines much more fuel-efficient than they are today (Bezdek and Wendling 2005, National Research Council 2002).

vehicles could compete with gasoline vehicles in these respects. The qualitative statements given to respondents likely increased the attractiveness of hydrogen fuel cell vehicles. However, an attribute that was omitted from both the IA part and the discrete choice experiment was the diversity of vehicle makes and models available on the market. Some previous studies have concluded that a limited selection of body types relative to conventional gasoline vehicles is a key factor preventing alternative fuel / technology vehicles from achieving significant market penetration (Leiby and Rubin 2003). Excluding this constraint might have artificially increased the appeal of hydrogen fuel cell vehicles, specifically for respondents that are partial to certain vehicle body types or brands.[23]

The two previous explanations could also apply to the almost identical companion study on HEVs (Mau, unpublished manuscript), but Mau did not find this dominance of ASCs. The final reason that might account for the attractiveness of hydrogen fuel cell vehicles relative to gasoline vehicles would also provide a way of accounting for the differences in results between this and the companion study. Perhaps the difference in dominance of the ASCs between the two studies is related to the radically new features of HFCVs – more radically new than HEVs' features. Respondents could have reacted favourably to the virtually unknown technology with a

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[23] When we asked respondents whether they would consider purchasing a hydrogen fuel cell vehicle even if their preferred vehicle body type was not available (Section 5 in the survey) between 75 to 90% said "yes", depending on their current primary vehicle body type. Those who said "yes" identified which body types they would consider. Respondents whose current primary vehicle was a compact highly favoured switching to a mid-size car over other alternatives, whereas those owning a mid-size car demonstrated more flexibility. Respondents currently owning a full size car showed a preference towards mid-sized vehicles. SUV and pick-up truck owners claimed to be willing to switch fairly evenly to all other vehicle body types except compacts. Mini-van owners appear more willing to switch to mid-size cars and SUVs than other body types. See Appendix for more detail.

futuristic quality, possessing a "disruptive" drive-train and steering mechanism. It is possible that respondents' attraction to hydrogen fuel cell vehicles is based on a perceived need to demonstrate a favourable attitude for disruptive technologies. Guerin (2003) emphasizes that consumers' desire to maintain status among a given group (friends, the panel, the researcher, for example) can determine the preferences they state but might have no impact on actual behaviour. As well, respondents' lack of familiarity with hydrogen fuel cell vehicle technology might have led to an assumption that all potential negative attributes are comparable to or better than the more familiar hybrid electric-gasoline vehicles. Thus, in accordance to the advice in Sondermann (2002) that marketers emphasize usefulness, convenience, and status factors of HFCVs, my survey design might have created a perception of higher status value relative to the companion study's HEVs, with little indication of the lower convenience values (with the exception of refuelling convenience).

Finally, the dominance of the ASC for hydrogen fuel cell vehicles could reflect the potential for dramatic switches to this vehicle technology, once it has attained a given level of development and acceptability. Bower and Christensen (1995) describe the commercialization of some disruptive technologies in the computing industry, and explain how established companies can fail to predict the mainstream appeal of these disruptive technologies, since these technologies tend to satisfy only niche market segments at the outset.[24] By definition, disruptive technologies present a set of attributes that existing customers might not value initially. However, improvements in valued and new attributes of this technology can rapidly match and outpace customers' demands, making it possible for the technology to penetrate the primary market. The potential for this phenomenon to occur with fuel cell vehicles might explain why established vehicle manufacturers, such as Daihatsu, Daimler Chrysler, Fiat, Ford, GM, Honda, Hyundai, Mazda, Mitsubishi, Nissan, Peugeot / Citroën, Renault, Toyota, and Volkswagen, are currently exploring prototypes of technology alternatives that focus on fuel cells (US Department of Energy 2004).

3.4.3 Assessing Responsiveness to Attribute Changes

Although the alternative specific constant has an important influence on my models' market share forecasts, assessing the role of other vehicle attributes in determining consumer choices of technology is important for policy analysis. For example, policy analysts might want to evaluate whether a subsidy programme targeting (1) consumers directly or (2) a transfer to vehicle manufacturers or fuel suppliers (to decrease costs seen by the consumer) would be more effective at increasing the uptake of hydrogen fuel cell vehicles. Table 3.11 shows the change needed in fuel cost, refuelling convenience, government subsidy, and warranty coverage to compensate for a $5,000 capital cost differential. For example, respondents would be willing to pay

[24] Among other examples, Bower and Christensen (1995) describe the chronology of innovations in the hard-disk drive industry that led to improvements in storage capacity, power consumption, portability, and cost per megabyte between 1976 and 1992. They point out that no one company was able to remain the leader in the transitions between a 14-inch architecture, to an 8-inch, to a 5.25-inch, to a 3.5-inch. These transitions represented shifts in market demands from mainframe computers, to minicomputers, to personal computers, to portable computers. At each stage, advances in the disruptive technology exceeded consumers' demands for storage capacity.

$5,000 more to purchase a HFCV over a gasoline vehicle provided weekly fuel costs were about $30 less. A seven to ten percent increase in refuelling convenience (percentage of stations with proper fuel) makes up for the $5,000 capital cost differential as well, and points to the value people place on convenience. This assessment also confirms that providing a direct subsidy to consumers has a greater potential to increase the market penetration of HFCVs than an equal reduction in capital cost. Innovators in particular value subsidies much more than any other group. A $1,300 subsidy equates to a $5,000 difference in capital cost. This means that direct subsidies to consumers may be most effective at early stages of market penetration.

Table 3.11: Equivalents to a $5,000 capital cost differential

Attribute	Model					
	Innovators	MS1 (0.03%)	MS2 (5%)	MS3 (10%)	MS4 (20%)	Laggards
Fuel cost (per week)	N/A	-$26.51	N/A	-$30.82	-$26.33	N/A
Government subsidy	$1,310.03	$2,920.63	$3,545.45	$2,684.93	$2,574.07	$2,569.43
Refuelling convenience (percentage)	+7%	+9%	+10%	+10%	+8%	+9%
Warranty coverage (years)	+5.4	+5.9	+8.9	+5.7	+4.5	+4.4
N/A = not applicable because the coefficient for fuel cost was not statistically significant at the 95% level.						

Another useful exercise is to assess how the probability of purchasing hydrogen fuel cell vehicles or gasoline vehicles can change as a function of changes in vehicle attributes (i.e., elasticity or "responsiveness"). This type of analysis allows us to compare the relative influence of each attribute on market share predictions. We use Equation 17 for this analysis.[25]

$$E = \frac{\partial MS_i}{\partial X_i} = \frac{\partial (e^{V_i} / \sum_j e^{V_j})}{\partial X_i} = \beta \cdot X_i \cdot MS_i (1 - MS_i) \qquad \textbf{Equation 17}$$

[25] The equation results from taking the first partial derivative of the MNL market share equation.

In this equation, β is the weighting coefficient pertinent to each attribute; X_i is the value of the attribute for technology i; and MS_i is the initial market share for technology i. Figure 3.6 through Figure 3.10 illustrate relative effects of changes in vehicle attributes on market share estimates from the models for innovators, majority (MS1), and laggards. [26] Since the model formulations are linear, elasticities for initial market shares between 50% and 100% are mirror images to those between 0% and 50%. This means that the elasticity estimated for an initial market share of 20% would be identical to the estimate for an initial market share of 80%, for example. Figure 3.6 shows the effects on market shares from changes in capital costs. Assuming an initial market share of 20%, a $25,000 decrease in capital costs increases the market share by about 75% for the majority, whereas the same change in capital costs increases the market share by 35% and about 50% for innovators and laggards, respectively. The difference between the trend lines for $40,000 and $15,000 represents the $25,000 decrease in capital costs.

[26] I present the results for MS1 to avoid confusion and repetition. Trends are similar for MS2, MS3, and MS4.

Figure 3.6: Capital cost elasticities

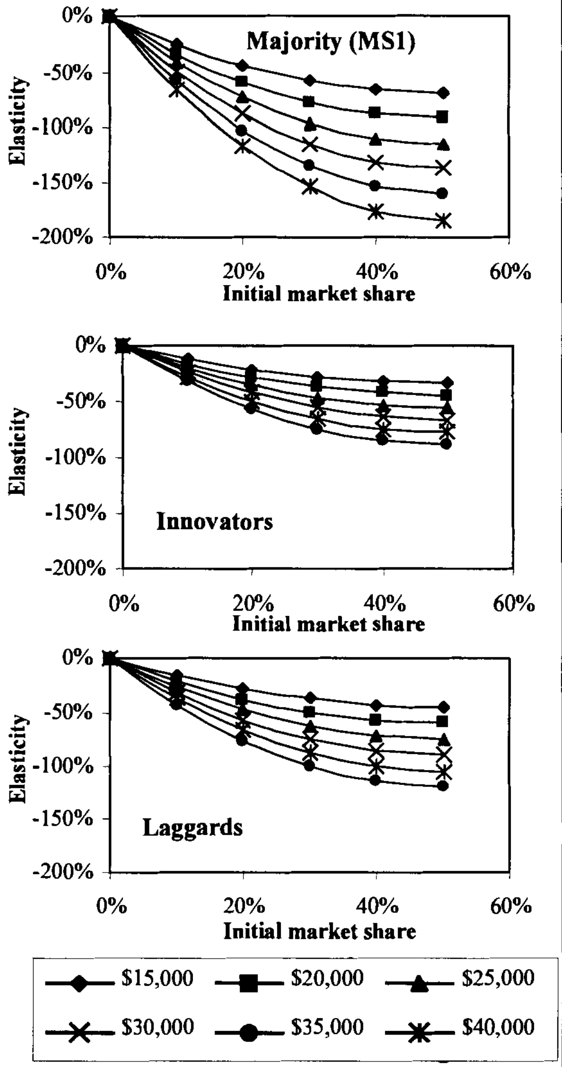


Figure 3.7: Refuelling convenience elasticities

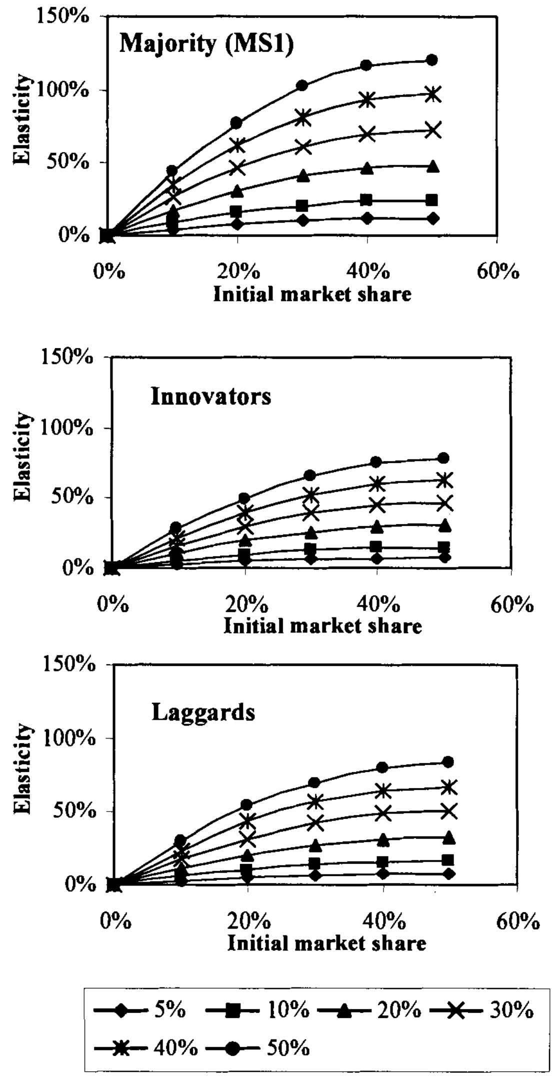


Figure 3.7 shows market share elasticities as a function of changes in refuelling convenience. Assuming an initial market share of 20%, a 40% increase in refuelling convenience increases the market share by about 60% for the majority, whereas the same change in refuelling convenience increases the market share by 40% and about 50% for innovators and laggards, respectively. The difference between the trend lines for

refuelling convenience of 10% and 50% represents the 40% increase in refuelling convenience.

In Figure 3.8 we see the effect of changes in government subsidy on market shares. Assuming an initial market share of 10%, a $4,000 increase in government subsidy increases the market share by about 10% for the majority. For innovators and laggards, the same change in government subsidy increases market share by about 12% and 8%, respectively. Using the same initial market share, increasing the warranty coverage by five years increases market shares by 7%, 4%, and 6%, for the majority, innovators, and laggards (Figure 3.9). Finally, increasing fuel costs by $50 per week decreases market shares by about 15% for the majority (Figure 3.10).

Overall, changes in capital cost result in the largest consumer response, followed by changes in refuelling convenience. The order of importance of government subsidy and warranty coverage across models varies. I could only calculate fuel cost elasticities for the majority models, since fuel cost turned out to be statistically insignificant (at the 95% level) and the wrong sign in the models for innovators and laggards.

Figure 3.8: Government subsidy elasticities

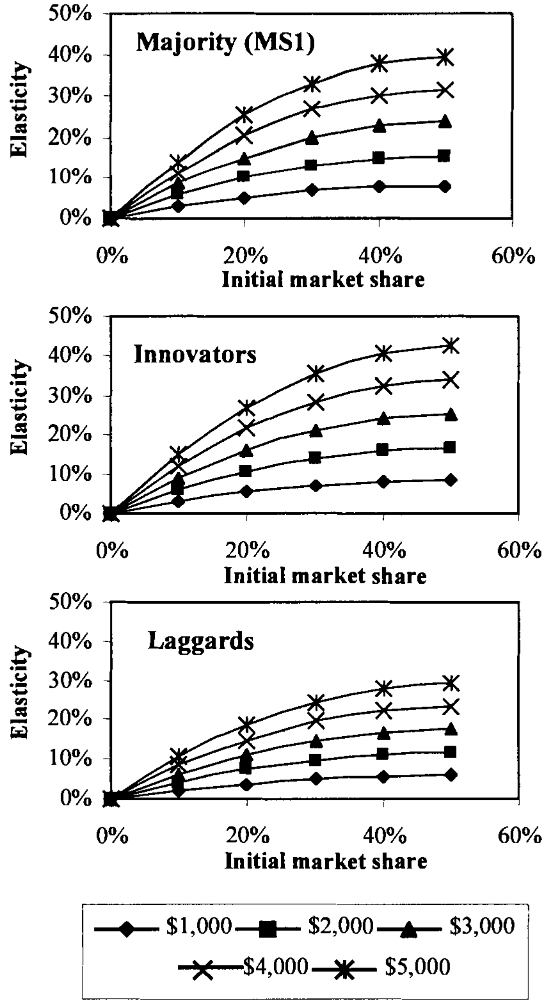
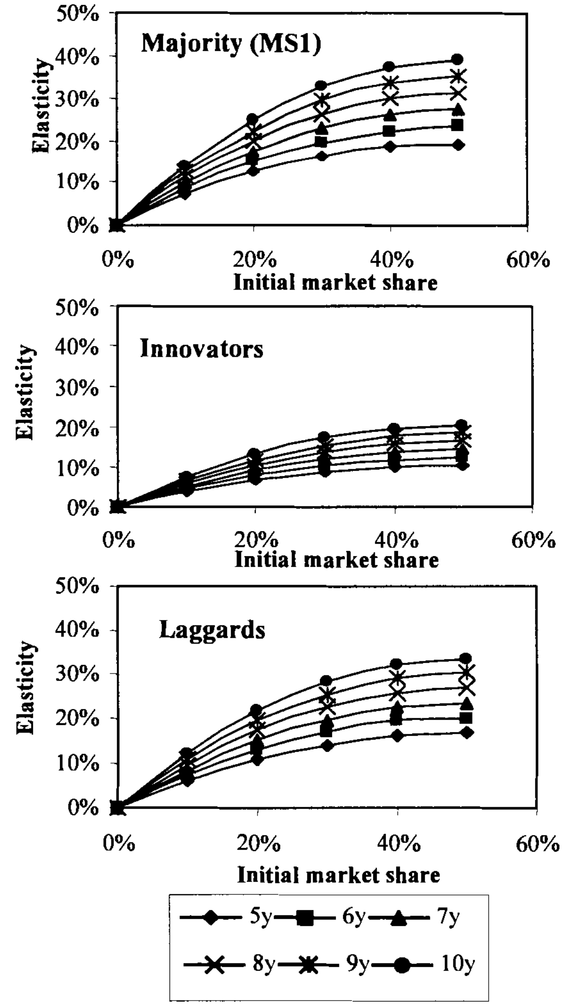
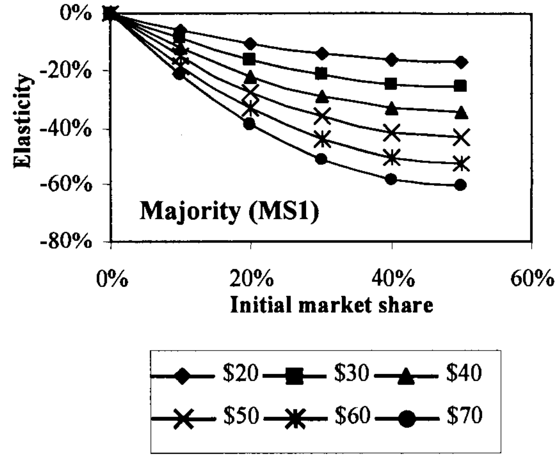


Figure 3.9: Warranty coverage elasticities



5y = 5 years of warranty coverage

Figure 3.10: Fuel cost elasticity



Differences among the three categories of technology adoption are worth noting. Representatives of the majority are more responsive to changes in vehicle capital costs and refuelling convenience than innovators or laggards, indicating that the wide adoption of hydrogen fuel cell vehicles in Canada is heavily dependent on manufacturers and policymakers being able to substantially reduce the upfront costs faced by the consumer and increase the fuelling infrastructure. Not surprisingly, laggards are not as responsive to changes in the levels of government subsidies as the majority and innovators. As well, implementing programmes that increase the warranty coverage of new vehicle technologies would likely increase the adoption rate of the majority and laggards, but would have less effect on innovators.

My results are comparable to the elasticity analysis in Horne's (2003) vehicle choice study. However, our results differ in the magnitude of elasticities for refuelling convenience, in particular. Assuming an initial market share of 20%, a change in fuel availability from 25% to 50% produced a 5% increase in new market shares in Horne's model, whereas the same increase in fuel availability in my model for majority (MS1) produced about a 38% increase in new market shares. Differences in experimental design can account for these discrepancies. Horne (2003) tested two levels of fuel availability, 25% and 50%, whereas my design included three levels of lower magnitude, 5%, 10% and 20% for hydrogen fuel cell vehicles. It seems that responsiveness to changes in fuel availability is not linear. Greene (1997) reached similar conclusions, stating that fuel availability is of key importance until a threshold of about 15% (percentage of stations with proper fuel) is reached. It is possible that the market share elasticities estimated for refuelling convenience from my models only apply at levels of refuelling convenience below 20%, whereas Horne's (2003) results might be more appropriate when testing the responsiveness to increases in refuelling convenience above 20%. Since one of the goals of my research is to inform CIMS with new behavioural parameters specific to hydrogen fuel cell vehicles, selecting an appropriate range of values each vehicle attribute can assume is important. This requires testing the robustness of results from the discrete choice models. I performed two types of analyses for this purpose, non-linearity and uncertainty analyses. In the following section I present the results of an analysis designed to test for non-linearities in the vehicle attributes from my choice experiment.

3.4.4 Testing for Non-linearities

The multinomial logit (MNL) model formulation I used assumes linear and additive relationships to estimate utility. Increases or decreases in utility resulting from changes in attribute values occur in a linear fashion. However, since all attributes in the experimental design have three levels I was able to estimate the effect of each attribute level by using dummy coding to treat the vehicle attributes as categorical variables (see Montgomery 1997, pp 109-110). I am only interested in assessing the effect of the difference in levels; therefore I arbitrarily set a base level for each attribute to zero. Table 3.12 reminds the reader of the levels used in the choice experiment and indicates which level became the baseline. For example, in the discrete choice experiment, the capital cost of hydrogen fuel cell vehicles could be 40%, 70%, or 90% higher than the cost of the conventional gasoline alternative (i.e., ratios of 1.4, 1.7, and 1.9). The baseline capital cost of the gasoline vehicle was the dollar amount the respondent stated to have paid for their current gasoline vehicle. As indicated on Table 3.12, I set 1.4 as the baseline level for the capital cost of hydrogen fuel cell vehicles. Therefore, the analysis I present here is intended to show whether changing the capital cost from 40% to 70% greater than the gasoline option affects utility the same way as changing the costs from 70% to 90%. After re-coding the data I re-estimated the six basic MNL models using LIMDEP 8.0, the results of which appear in Figure 3.11 through Figure 3.15. In this series of figures, the attribute levels are on the x-axis and beta coefficients on the y-axis. Confidence intervals are a multiple of the standard error associated with each beta coefficient (±2 times the standard error).[27]

[27] When confidence intervals for a given data point substantially overlap with those of another data point, I assume that there is no difference between the two results.

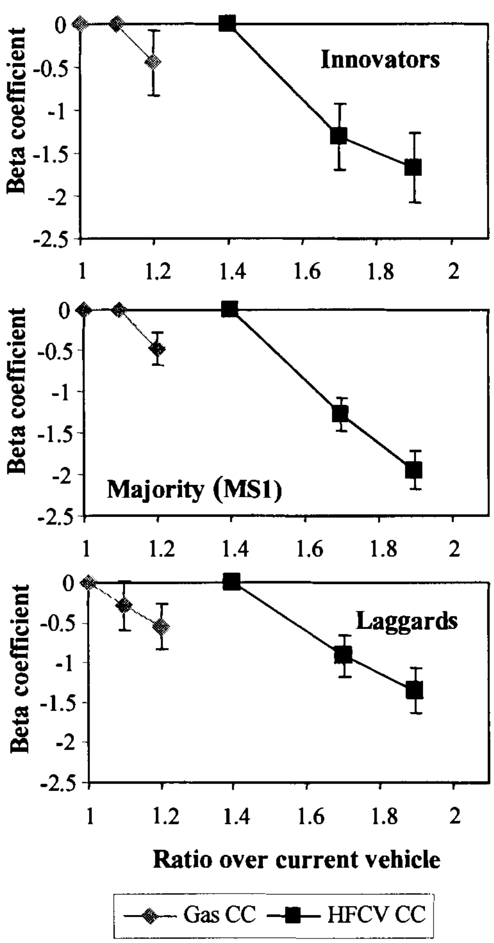
Table 3.12: Treatment of vehicle attributes

Attribute	Level	Explanation
Capital cost (HFCV)	1.4 (baseline)	Value is relative to the capital cost respondents paid for their current vehicle. 1.4 = 40% greater than the capital cost of respondents' current vehicle.
	1.7	
	1.9	
Capital cost (gasoline)	1 (baseline)	Value is relative to the capital cost respondents paid for their current vehicle. 1 = the capital cost of respondents' current vehicle.
	1.1	
	1.2	
Fuel cost (gasoline)	1 (baseline)	Value is relative to respondents' weekly fuel costs. 1 = respondents' weekly gasoline costs.
	1.1	
	1.25	
Government subsidy (HFCV)	0.05 (baseline)	Value is relative to the capital cost respondents paid for their current vehicle. 0.05 = a subsidy amounting to 5% of the capital cost of respondents' current vehicle.
	0.1	
	0.2	
Refuelling convenience (HFCV)	0.05 (baseline)	Value is a proportion of stations with proper fuel for HFCVs. 0.05 = 5% of stations have the proper fuel.
	0.1	
	0.2	
Warranty coverage (HFCV)	5 (baseline)	Value is number of years of warranty coverage.
	8	
	10	

Figure 3.11 shows the results for capital costs, with the capital cost ratios used in the choice experiment represented on the x-axis. The grey trend lines show the effects on utility resulting from capital cost increases of 10% (ratio of 1.1) and 20% (ratio of 1.2). The three graphs show that increasing the capital cost by 10% has no effect on utility for innovators and the majority, but might have a negative effect on utility for laggards. Increasing the capital cost between 10% and 20% has negative effects on utility for the three groups. The black trend line shows the effects on utility from changes in capital costs between 40% and 90% greater than the capital cost consumers paid for their current vehicle. The three graphs show that, within these ranges, a linear relationship exists between capital cost premiums and utility.

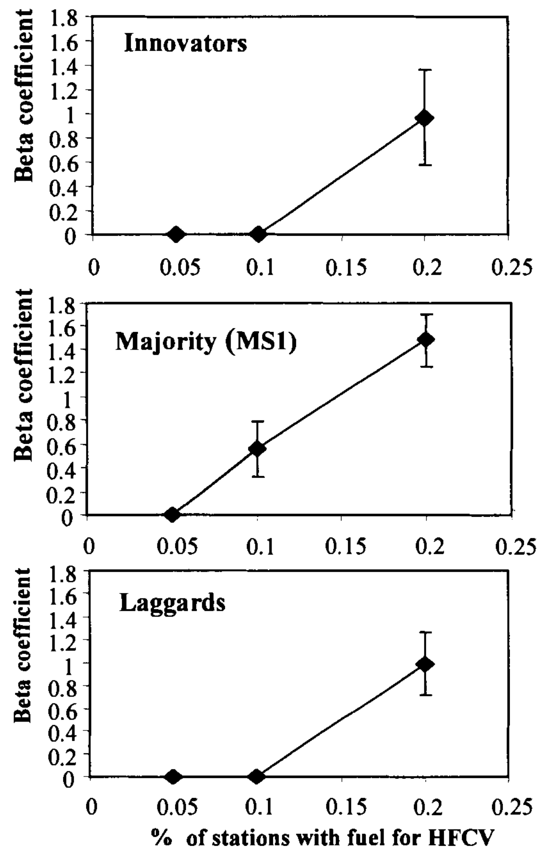
Figure 3.12 shows the effects on utility from changes in refuelling convenience, restricted to the levels used in the choice experiment. In this case, the results indicate that, increasing the percentage of stations with proper fuel for HFCVs from 5% to 20% increases utility in a linear fashion for the majority but not for innovators or laggards. For the two last groups, increasing the percentage of stations with proper fuel from 5% to 10% has no effect on utility, whereas increasing the percentage of stations with proper fuel above 10% has a positive effect on utility.

Figure 3.11: Non-linearities in capital cost



CC = capital cost
Confidence intervals are ± 2 standard error*

Figure 3.12: Non-linearities in refuelling convenience

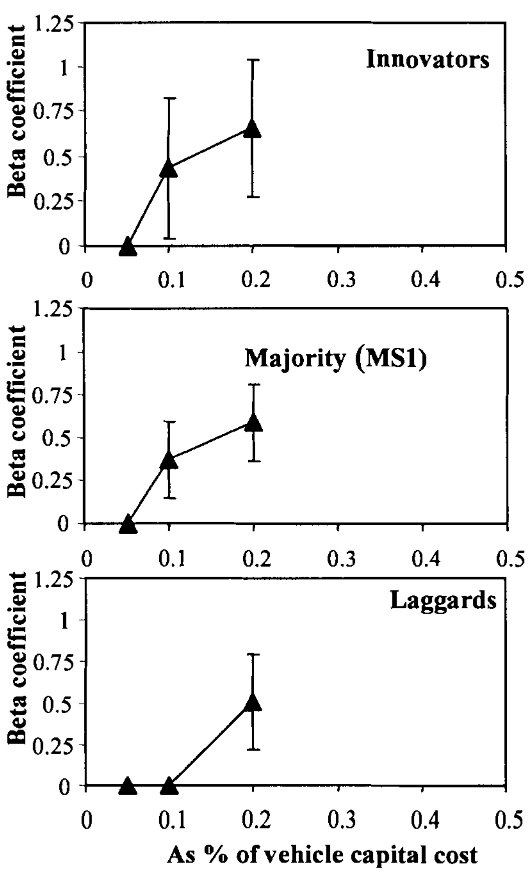


Confidence intervals are ± 2 standard error*

Figure 3.13 shows the effects on utility from different levels of government subsidy. In the choice experiment, government subsidy could be 5%, 10%, or 20% of the capital cost respondents paid for their current vehicle. The results indicate that innovators and the majority value subsidies in this range linearly, whereas laggards have a greater utility for subsidies between 10% and 20% (of vehicle capital cost) than for subsidies below 10%. That is, a subsidy of less than 10% of a vehicle's purchase price would not be enough of an incentive for a laggard.

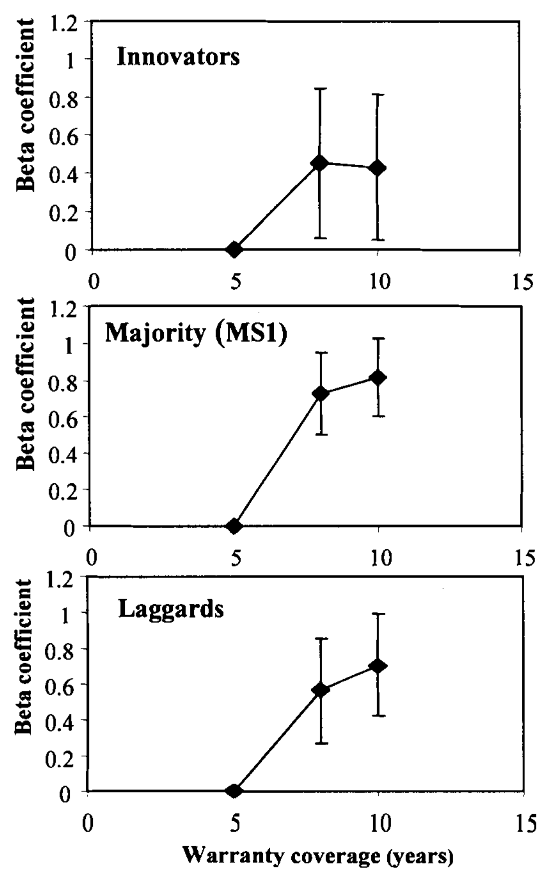
Figure 3.14 illustrates the effects on utility from the different levels of warranty coverage included in the choice experiment. The three graphs show that consumers do not seem to value increases in warranty coverage beyond 8 years. That is, increasing warranty coverage from 5 to 8 years has a positive effect on utility, but there is little to no difference in utility from increasing warranty coverage from 8 to 10 years.

Figure 3.13: Non-linearities in government subsidy



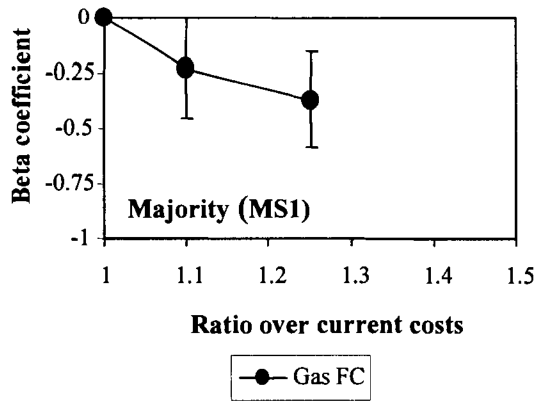
Confidence intervals are ± 2 standard error*

Figure 3.14: Non-linearities in warranty coverage



Confidence intervals are ± 2 standard error*

Figure 3.15: Non-linearity in fuel cost



FC = fuel costs
Confidence intervals are ± 2 standard error*

Finally, Figure 3.15 illustrates the effect on utility from the different levels of fuel cost included in the choice experiment. The fuel cost ratios are relative to respondents' weekly gasoline costs. The graph illustrates that a 10% premium on fuel cost might not affect utility for the majority, but an increase between 10% and 20% has a negative effect on utility. The size of the confidence intervals for data points in this figure, as well as in Figure 3.14 and Figure 3.13, indicate that these results are very uncertain. Therefore, the reader should be cautious when drawing any conclusions from the observations I present.

This test for non-linearities helped to determine the range of values for refuelling convenience and warranty coverage that I would later use to parameterize the declining intangible cost function for CIMS. In Section 2.3, I explained that estimating intangible costs from results of discrete choice models requires selecting values by which to weight the coefficients for non-monetary attributes (X_n in Equation 7). In theory, I could estimate the intangible costs associated with hydrogen fuel cell vehicles and gasoline vehicles using any value for refuelling convenience and warranty coverage. However, the results from these non-linearity analyses and the elasticity analyses I presented previously indicate the following. 1) I am most confident about using values for refuelling convenience between 0% and 20% to estimate intangible costs. In this range, there appears to be a linear relationship between refuelling convenience and utility (Figure 3.12 - majority). I have less confidence in the intangible costs I estimate using values for refuelling convenience over 20%, given the differences between my elasticity results for this vehicle attribute and Horne's (2003). To minimize the errors introduced into the intangible cost estimates, I avoided using values for refuelling convenience over 20% for hydrogen fuel cell vehicles. However, refuelling convenience is always assumed to be 100% for gasoline vehicles. Thus, the intangible costs or benefits associated with this type of vehicle are likely to be overestimates - since we have seen that the marginal value of refuelling convenience decreases past 20% of stations with proper fuel. 2) To estimate the intangible costs of warranty coverage, I use values between 5 and 8 years, as the non-linearity analysis shows that a warranty coverage exceeding 8 years has little to no effect on utility (Figure 3.14).

3.4.5 Assessing the Uncertainty in DCM Coefficients

The results I have presented so far use the maximum likelihood estimates (MLEs) for each vehicle attribute in the DCM, given the stated preference data collected. By definition, the MLEs explain the data better than other combinations of β coefficients; however, alternative combinations of coefficients -- although less likely – could also fit the data reasonably well. To determine how confident we are in the MLEs, we need to consider a range of alternative combinations of β coefficients and their probability of occurrence. In the following paragraphs, I describe the method and results of my analysis to quantify the uncertainty in parameter estimates.

The MLEs provided by LIMDEP 8.0 are those that maximize the log-likelihood function shown in Equation 18. N is the number of observations, and $P_{n,j}(\beta)$ is the probability given by the (multinomial logit) model to a choice made by respondent j at observation n, given the combination of β coefficients. LIMDEP finds the best-fit β coefficients by performing an iterative search over a range of β coefficients, which is accomplished by taking the first and second derivatives of the log likelihood function. This optimization procedure is efficient, but it does not give us an indication of how much confidence we should place on the optimal parameters; we only know that the coefficients estimated by LIMDEP are the most likely.

$$LL(\beta) = \sum_{n=1}^{N} \frac{\ln(P_{n,j}(\beta))}{N} \qquad \textbf{Equation 18}$$

To assess the uncertainty in the best-fit coefficients for each discrete choice model, I took a Bayesian approach. I solved Equation 18 for the six vehicle attributes in the utility function by independently varying each parameter according to a range of uncertain values for β.[28] I assumed a uniform prior probability to transform the likelihoods associated with the various β coefficient values into posterior probability distributions. The result of this analysis is a series of "conditional" probability density functions for the six vehicle attributes. In other words, I examined the likelihood of a given parameter value assuming that the other five parameters were the MLEs. I

[28]The six vehicle attributes are capital cost, fuel cost, refuelling convenience, warranty, government subsidy, and the alternative specific constant for hydrogen fuel cell vehicles.

adjusted the scope of possible parameter estimates until the posterior probabilities at the two tails ends of each probability density function were 0% or 1%, where possible. The following figures (Figure 3.16 to Figure 3.21) contain the results of the uncertainty analysis for one multinomial logit model (majority - MS3). The trends observed for this model are consistent across all models.

This analysis provides information the t-ratios in Table 3.3 do not convey. Capital cost has the highest t-ratio among the vehicle attributes, meaning that we are confident that this attribute has the greatest influence on vehicle choices. However, Figure 3.16 shows that the range of possible values this coefficient can assume is wide. Possible coefficient values are on the x-axis; these values are relative to the MLE, which I set to zero. Although this MLE's posterior probability is 20%, possible β values range from 3 times less to 10 times more than the MLE.

Figure 3.16: Probability density function - capital cost coefficient

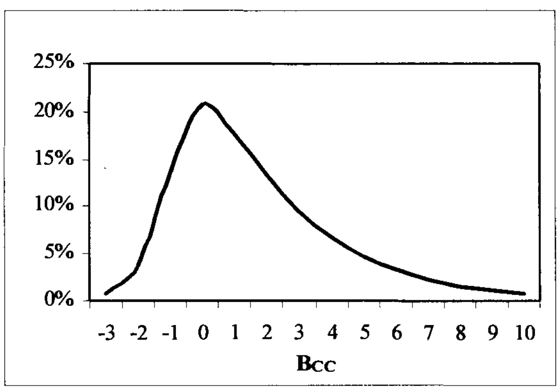
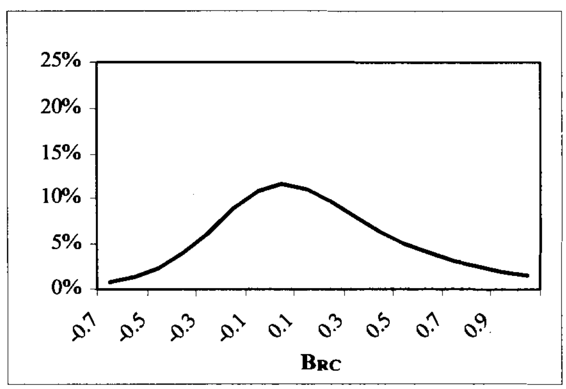


Figure 3.17: Probability density function – refuelling convenience coefficient



We are more confident in the MLEs for refuelling convenience and the alternative specific constant, given the narrower range both coefficients can take on. The probability density function for refuelling convenience indicates that possible coefficient values range from 0.7 times less to about 0.9 times more than the MLE (Figure 3.17). Similarly, the value of the coefficient for the alternative specific constant could be could be 100% less or about 0.7 times more than the MLE (Figure 3.18). Still, the probability associated with the MLEs for both vehicle attributes is less than 10%.

Figure 3.18: Probability density function - alternative specific constant (HFCV)

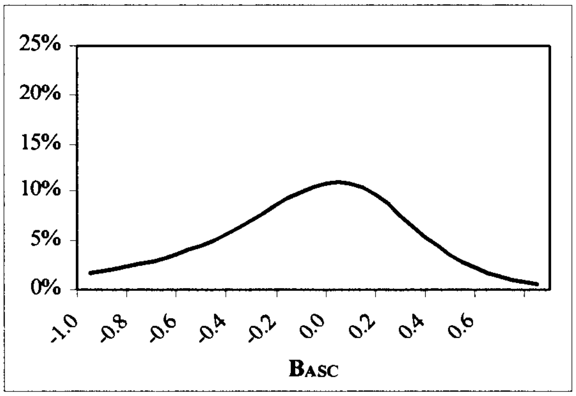
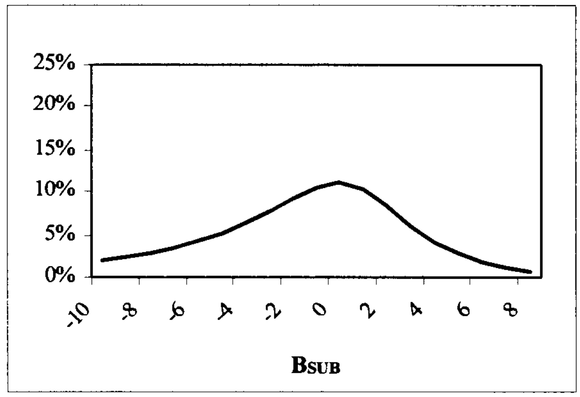


Figure 3.19: Probability density function - government subsidy coefficient



Government subsidy and warranty coverage contribute less to utility than capital cost, refuelling convenience and the alternative specific constant (Table 3.3). As well, Figure 3.19 and Figure 3.20 show that we are very uncertain about the deterministic estimate for these two coefficients. The probability of occurrence of both MLEs is less than 10%, and the range of possible values could be 10 times less to about ten times more than the MLEs. Finally, the probability distribution for fuel cost is so diffuse we cannot claim to know anything about its true parameter value (Figure 3.21).

Figure 3.20: Probability density function - warranty coverage coefficient

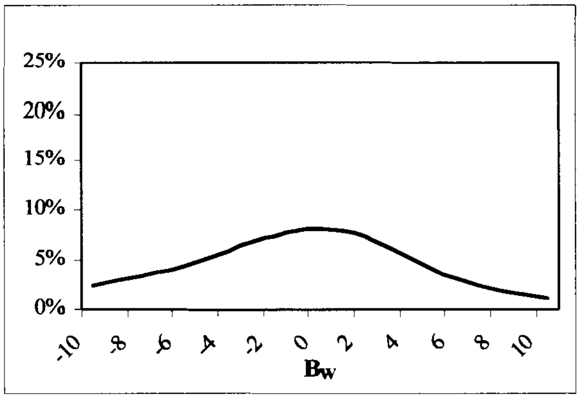
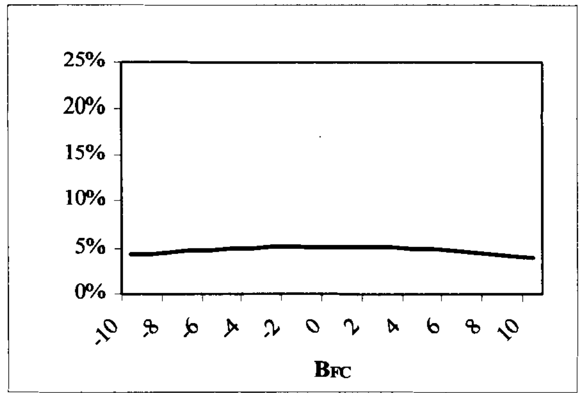


Figure 3.21: Probability density function - fuel cost coefficient



The parameter estimates from my models are considerably less certain than those in Horne's (2003) similar vehicle choice model.[29] The main differences in design that might have affected the response quality are: 1) Horne's experiment included five vehicle technologies instead of two; 2) Horne divided the choice sets in his experiment so that each respondent only answered four questions (versus the 18 in my experiment); 3) differences among technologies in capital cost never surpassed 20% in Horne's attribute values, whereas it could reach 90% (85% netting out the subsidy) in mine. Although the lower number of alternatives described in Points 2 and 3 seems intuitively to provide for an increased confidence in Horne's study, the higher number of alternatives described in point 1 seems to provide for the reverse. These are only speculations. The main implication of the analysis presented in this section is that the uncertainty inherent in the coefficients for capital cost, fuel cost, refuelling convenience, government subsidy, and warranty coverage translates into uncertainty in the

[29] The results of Mau's (unpublished manuscript) uncertainty analysis for his study on preferences for hybrid-electric vehicles closely match my findings.

behavioural parameters (for CIMS) I will later estimate. I discuss ways of portraying this uncertainty in the next chapter.

CHAPTER 4 DYNAMIC CONSUMER PREFERENCES IN CIMS

Policymakers require a range of information about the likely market penetration of new consumer products and the likely success of policies designed to influence consumer behaviour with respect to these products. Some pieces of information include: 1) how individuals and businesses make decisions in response to policies; 2) what the likelihood is of individuals and businesses to behave a given way; 3) whether the way individuals and businesses make decisions change (and, if they do, how); and 4) how policies targeting one sector of the economy (or one type of behaviour) might affect other sectors. Discrete choice models (DCMs) have been used to explore the first two of these questions (Ben-Akiva and Morikawa 2002, Hensher 2002, Ewing and Sarigöllü 2000), and Mau (unpublished manuscript) and myself used DCMs to investigate the third question. However, the fourth question requires different analytical tools. For example, an analyst might want to assess the impact of a subsidy programme designed to increase the take-up of low greenhouse gas-emitting passenger vehicles. The subsidy programme might have a high probability of increasing the desired take-up, but would it also induce an increase in single-occupancy vehicle use at the expense of other, more benign modes of personal transport? Or, would the marked penetration of low GHG-emitting vehicles result in an increase in GHGs in other economic sectors, such as electricity generation, fuel processing, or manufacturing? CIMS, a technology-specific energy economy model, can provide the integrative framework required to investigate the potential outcomes of alternative policies more fully. When informed by behaviourally realistic analysis, CIMS can also keep an account of technology choices in the long run, the evolution of these choices, and feedbacks within and among economic sectors.

In this chapter, I apply the methods outlined in Sections 2.3 and 2.4 to transform the results of the majority multinomial logit (MNL) models into behavioural parameters that are compatible with CIMS. As explained in Section 3.3.2, I limit this study component to the results from the majority models on the assumptions that (1) the results from these models are representative of the average Canadian urbanite's preferences and (2) this population segment is the primary target of policies. The section has three main parts. First, I present and discuss the *r* (discount rate), and *v* (variance or market heterogeneity) parameters resulting from this research. Second, I show the intangible costs (*i*) associated with the two vehicle technologies under different assumptions, discuss the success of the experimental treatment in capturing consumer preference dynamics for hydrogen fuel cell vehicles, and show the parameters estimated for the declining intangible cost function (DIC) in CIMS. Third, I test CIMS' capacity to model the market evolution of hydrogen fuel cell vehicles (HFCVs) by simulating various policies aimed at increasing the market share of HFCVs relative to conventional gasoline cars. Both car technologies are contained within the "new car competition node" in CIMS. I ignore the other car technologies that directly compete with gasoline cars and HFCVs within this node.[30] A more realistic assessment would activate either the declining capital cost function or declining intangible cost function (or both) for all vehicle technologies expected to have a long-term presence or have the ability to

[30] The following vehicle technologies / fuels compete under the "new car" node in CIMS: high efficiency gasoline, low efficiency gasoline, propane, natural gas, diesel, methanol, ethanol, battery-electric, gasoline electric hybrid, and hydrogen fuel cell.

drastically change the level of greenhouse gas (GHG) emissions from personal urban transportation in the long term.

4.1 Reporting Static Behavioural Parameters for CIMS

In CIMS the private discount rate (*r*) and the variance (*v*) parameter are static, which means that neither change during the 30-year simulation period.[31] This implies that I had to base the estimation of *r* and *v* on the results from only one of the four majority models corresponding to the four market share groups. I calculated private discount rates (*r*) for the four majority models first. In the market share 2 model, fuel cost was not a significant attribute in decision-making. Discount rates estimated from this model are atypically high, which led me to eliminate this model as a basis for estimating the two static behavioural parameters.[32] Table 4.1 shows *r* values calculated for the three remaining majority MNL models using Equation 6 over a range of technology lifespans. Discount rates estimated from the three models were within 30%. I chose the model that yielded the most conservative (highest) discount rates to calculate the *v* parameter. My assumption in choosing the most conservative outcome was that the average Canadian would have a relatively high discount rate when making decisions about unknown technologies. The model for market share group 3 gave the highest private discount rates, and therefore I used this market share group to calculate *r* and *v*.

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[31] The *v* parameter establishes the extent to which lifecycle costs determine new market shares. A low value indicates that even technologies with relatively high lifecycle costs can achieve some market penetration; whereas, a high value means that technologies with the lowest lifecycle costs will dominate the competition.

[32] Private discount rates range from 87% to 91%, depending on the technology lifespan assumed.

Table 4.1: Private discount rates from Majority MNL models

Technology lifespan (n)	Private discount rate		
	MS1 (0.03%)	MS3 (10%)	MS4 (20%)
5	3%	11%	0.00%
8	14%	22%	11%
10	17%	24%	14%
16	20%	27%	18%
18	21%	27%	18%
20	21%	27%	19%
25	21%	27%	19%
30	21%	27%	19%
50	21%	27%	19%
95	21%	27%	19%

As shown on Table 4.1 the marginal change in discount rates as a function of technology lifespan tapers off between 16 and 18 years. Thus, dividing the capital cost coefficient by the fuel cost coefficient provides a valid estimate for *r*, given that CIMS assumes a 16-year lifespan for vehicles. Using this simplification and sampling from the joint probability distribution for the two coefficients (capital cost and fuel cost), I estimated a most likely discount rate for market share group 3 of 27.6%, with 95% of the possible estimates occurring between 0.6% and 78.1%. This estimate is consistent with those of other vehicle choice studies, both within and external to the Energy and Materials Research Group at Simon Fraser University. Horne (2003) reported a discount rate of 22.6%, well within the ranges in Train (1985) and Ewing and Sarigöllü (2000). Similarly, in the companion study to mine, Mau (unpublished manuscript) estimated the most likely discount rate from his vehicle choice study to be 21.8%, the most probable values falling between 10% and 30%. Note that Mau did not base his final results for *r* and *v* on the model yielding the highest private discount rates; instead, he used the model for market share group 1 to calculate these.

The solution for v that most consistently matched the market share forecasts from both the DCM for market share group 3 and that group's integration into CIMS is 5.16. Recall that a low value of v means that even technologies with high costs can capture a portion of the new market share (see Figure 1.1). My estimate for v is lower than the factor of 10 that CIMS currently assumes for vehicle choice, but it is higher than the value of 2.9 estimated by Horne (2003). It is almost twice as high as the value Mau (unpublished manuscript) reports from his hybrid electric vehicle choice study, despite almost identical experimental designs. To investigate whether the reason for the difference in v values is due to differences among market share groups, I found a solution for v that scaled the DCM for market share group 4 to CIMS, using the most likely discount rate for that market share group (22.1%). The best-fit value for v resulting from this exercise was fairly consistent with my first solution, which indicates that consumers make investment differently for hybrid electric vehicles than for hydrogen fuel cell vehicles.[33] This difference is expressed in the dominance of the alternative specific constant in forecasting the split between hydrogen fuel cell vehicles and gasoline vehicles using my MNL models.

Speaking more broadly, every stated preference study conducted by EMRG researchers has suggested that markets are more heterogeneous than CIMS currently portrays them (Horne et al. forthcoming, Rivers and Jaccard forthcoming, Jaccard and Dennis forthcoming, Mau unpublished manuscript, and this study). However, these studies (including my own) do not provide a measure of uncertainty around their respective estimates for v, since we do not calculate this parameter directly from the MNL models, and other techniques involving iterative sampling are beyond the scope of

[33] The v parameter resulting from the MNL model for MS4 is 5.80.

our studies. In other words, we have empirical evidence pointing to greater market heterogeneity than CIMS assumes for certain technology competitions, but we are unsure about the magnitude of the variance. Nor can we extrapolate our findings to technology choices outside the contexts or sectors of our respective studies with much confidence. [34]

4.2 Accounting for Preference Dynamics in CIMS

In Section 2.2.5 I explained the use of the market share ratio of hydrogen fuel cell to gasoline vehicles as a blocking variable, and I described the type of Information Acceleration (IA) respondents were subjected to during the survey in order to implement the blocking. The *ex-ante* assumption underpinning the experimental design was that the IA treatment would influence people's responses to the choice experiment. The hypothesis was that people's value for hydrogen fuel cell vehicles would increase as the market share of that technology, and their awareness of the growing market share, grew. However, as we saw in Section 3.4, forecasts resulting from the MNL models for the four majority groups (MS1, MS2, MS3, and MS4) do not follow a neat trend. In fact, we generally do not observe a significant difference in forecasts. Nevertheless, we do observe differences among the market share groups in the intangible costs associated

[34] For example, Horne (2003) and I both estimated behavioural parameters for CIMS from vehicle choice experiments. However, the decision environment of our respective studies differed. One aspect that differed was the number and types of alternatives respondents had to choose from. In Horne's study respondents had to choose among five vehicle technologies. It is likely that respondents had very little prior information about two of these technologies, but had been exposed to the rest. In my study, respondents chose between two technologies. On average, they had no prior knowledge about hydrogen fuel cell vehicles. My experiment forced them to decide between a technology they were very familiar with and a completely unknown technology. Because these fundamental differences in experimental design between Horne's study and mine produce different results, I would be cautious in applying my results to other vehicle choices, let alone sectors outside personal transportation.

with hydrogen fuel cell and gasoline vehicles, but not in the way I had expected at the outset. The following example shows the market share forecasts (Figure 4.1) and intangible costs (Figure 4.2 and Figure 4.3) corresponding to the scenario shown in Table 4.2 (non-monetary attributes are in italics). For comparison, I also include results from the models for innovators and laggards. I calculated the intangible costs using the procedure in Section 2.3 (Equation 7). In Figure 4.2 and Figure 4.3, negative numbers indicate intangible benefits. Figure 4.2 shows that people in all groups attach huge intangible benefits to both gasoline vehicles and hydrogen fuel cell vehicles. For example, assuming the values for non-monetary attributes in Table 4.2, respondents in market share group 4 attach intangible benefits to gasoline vehicles and hydrogen fuel cell vehicles of about $70,000 and $67,000, respectively. These intangibles are high because the coefficients for refuelling convenience and the alternative specific constant (only applicable to HFCV) are four to five orders of magnitude greater than the capital cost coefficient. Since we are interested in the intangible difference that people perceive between the two vehicle technologies, Figure 4.3 provides a more useful representation than the absolute costs. Again, taking market share group 4 as an example, Figure 4.3 shows that consumers implicitly value gasoline vehicles more than hydrogen fuel cell vehicles, perceiving an intangible cost of about $2,600.

Table 4.2: Vehicle attributes for market share forecasts and intangible costs

Attributes	Gas	HFCV
Vehicle capital cost ($)	17,100	29,510
Fuel cost ($ / week)	25	25
Government subsidy	0	2,000
Refuelling convenience	100%	10%
Warranty coverage (years)	5	8
Is it HFCV? (1=yes, 0=no)	0	1

Figure 4.1: HFCV forecasts

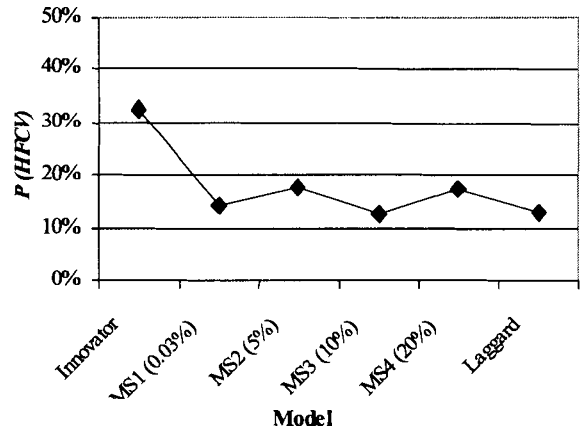


Figure 4.2: Intangible costs - gas and HFCV

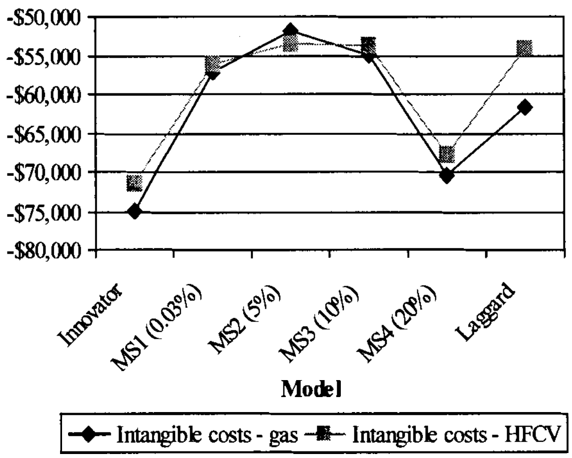
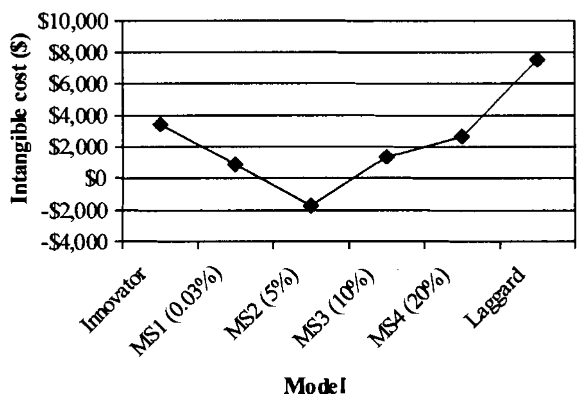


Figure 4.3: Difference in intangible costs (HFCV - gas)



Instead of observing a declining trend in intangible costs for HFCVs relative to gasoline cars from MS1 to MS4, Figure 4.3 shows that respondents in MS2 perceive the lowest intangible costs of all the adoption groups, including innovators and laggards. This v-shaped pattern is consistent over the range of values for refuelling convenience and warranty coverage discussed in Section 3.4.4 (the ASC can only be 1 or 0). As previously mentioned, refuelling convenience and the ASC are the two non-monetary attributes that dominate the estimate of intangible costs. So, the only way we would see the expected trend of declining intangibles for HFCVs from MS1 to MS4 is if the contribution to utility from refuelling convenience declined and that for the ASC increased. Such is the case in Mau (unpublished manuscript), where the difference in intangible costs between hybrid electric and gasoline cars decreases from MS1 to MS4 as a function of changes in the way market share groups value cruising range and factors associated with gasoline vehicles left out of the choice experiment (i.e., the alternative specific constant).[35] Mau's monetized estimates for cruising range and the ASC indicate that both the value for cruising range and the value intrinsic to gasoline vehicles both decline in response to the experimental blocking variable. I propose three explanations to account for the difference in intangible cost dynamics between my study and Mau's. The three explanations inter-relate.

First, at present HFCVs are more of a concept than a tangible consumer good, increasing the hypothetical nature of the choice experiment. Although advances in this vehicle technology are occasionally noted in mainstream media and politician's pronouncements in support of "the car of the future", consumers know very little about this technology and how its commercialization might proceed. At most, HFCVs symbolize the techno-solution to greening the transportation sector without sacrificing our personal freedom. For some respondents, the information provided during the IA portion of the survey might have been their first exposure to HFCVs, which was unlikely to be the case with Mau's study of hybrid electric vehicles. I suggest that my choice experiment was too demanding an exercise given respondents' limited knowledge of hydrogen fuel cell vehicles. Literature on decision-making under

[35] Mau used cruising range instead of refuelling convenience. He also included a constant specific to gasoline vehicles in the utility function. The remaining monetary and non-monetary attributes are identical to mine.

uncertainty shows that people often devise strategies to simplify the decision task (Payne et al. 1993). In administering a choice experiment and using a multinomial logit (MNL) utility formulation, I assumed that respondents would explicitly make trade-offs among the attribute values presented in each question. In practice, respondents might have taken a hierarchical approach to deciding between an HFCV or gasoline car, which takes less effort than considering all the attributes independently. For example, a given respondent's decision rule might have been to choose the gasoline car unless the HFCV's refuelling convenience was 20%; another respondent might have chosen HFCVs provided refuelling convenience did not drop below 10% and the capital cost differential did not exceed 40%. Respondents from the four market share groups could have focused on using this type of heuristic irrespective of the blocking variable.

Second, I propose that the information pieces under the IA portion of the survey created high (?) or false (?) expectations with respect to the refuelling infrastructure for hydrogen fuel cell vehicles. These expectations could have confounded the effect of the blocking variable with respondents' utilities for refuelling convenience. For example, the scenario we described to respondents in MS4 was that one out of five Canadians owned a hydrogen fuel cell vehicle. Yet, the choice experiment included situations in which only 1 out of 20 and 1 out of 10 stations offered the proper fuel for HFCVs, which they may have perceived as inadequate given the market conditions described to them earlier. This phenomenon could have occurred alone or in combination with the hierarchical decision-making strategy I propose above.

The third possible explanation relates to the uncertainty associated with hydrogen fuel cell vehicles, and it is merely speculative. The difference in the trends of intangible costs for hydrogen fuel cell vehicles versus hybrid electric vehicles might be attributable to the prospect of adopting a disruptive versus an evolutionary technology. With a disruptive technology consumers have to learn how to use and maintain the product, which imposes significant transaction costs. Perhaps this transaction cost greatly outweighs potential technology-specific benefits, and people will only consider making the investment once the product's attributes reach some threshold level of development or the product attains a crucial milestone of market acceptance.

The three explanations above are the most obvious, but many more might exist. I conclude that the experimental treatment did not achieve the intended effect of depicting preference dynamics in response to market penetration dynamics. However, this does not mean consumers might not be susceptible to the "neighbour effect" when it comes to switching to HFCVs; my experiment just failed to provide the empirical evidence for it. Indeed, intuition and a wide range of literature on decision-making under uncertainty tell me that imitation is likely to be a valid influence in the adoption of this disruptive vehicle technology (Janssen and Jager 2001). In Section 5.3.1, I recommend improvements to the experimental design in my research to facilitate the success of future research in EMRG on preference dynamics for disruptive vehicle technologies.

For reasons explained above, I cannot directly use the intangible cost estimates from my four majority discrete choice models to estimate the declining intangible cost (DIC) function. But, at the very least, two reasons exist for illustrating how this might be done. First, future EMRG researchers might benefit from alternative descriptions of the same method, as I benefited from comparing among Horne's (2003), Rivers' (2003) and

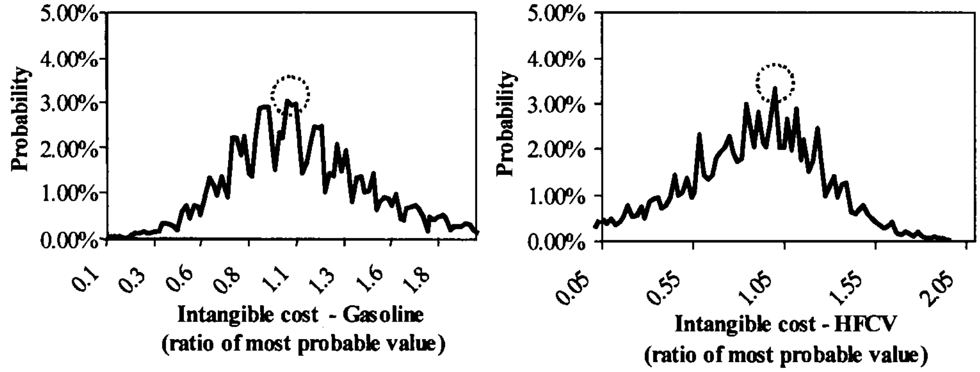
Sadler's (2003) explanations. Mau and I use the same method to convert intangible cost estimates from discrete choice models into dynamic intangible parameters in CIMS, yet our descriptions and level of detail are different. Second, one of my research objectives was to be able to simulate the long term outcomes of policies aimed at increasing the adoption of HFCVs in Canada. Currently, information of this type that is grounded in empirical research is unavailable. The intangible cost estimates from my research are "ball-park" figures, and provide and indication of (1) the magnitude of intangible costs associated with switching from gasoline cars to HFCVs and (2) the magnitude of the difference in these perceived intangible costs among groups of people subjected to different market conditions. In the next section I describe the assumptions and values I used to illustrate the estimation of parameters for the declining intangible cost function in CIMS.

4.2.1 The Declining Intangible Cost Function

Once I decided on the data points I would use to illustrate the estimation of the parameters for the declining intangible cost function (DIC), I followed the procedure described in Section 2.4. Prior to presenting these parameter estimates and the assumptions behind them, I briefly discuss the uncertainty associated with the DIC derived from research of this type. The discussion would be equally relevant had my research design yielded empirical evidence in support of the "neighbour effect". Uncertainty comes from two major sources (1) the DCM coefficients and (2) the experimental treatment.

Recalling from Section 3.4.5, the probability distributions for the coefficients from the four models for majority are fairly diffuse. In the best of cases the maximum likelihood estimate (MLE) is only 20% probable. Since the intangible cost estimates derive from comparisons between the coefficients for non-monetary attributes and capital cost, our confidence in these estimates depends on our confidence in the DCM coefficients. For example, Figure 4.4 shows the probability distributions corresponding to the estimates for intangible costs for gasoline and hydrogen fuel cell vehicles from the DCM corresponding to market share group 4. These distributions for both vehicle technologies were constructed by simultaneously sampling from the posterior probability distributions for refuelling convenience, warranty coverage, and the ASC, which I discussed in Section 3.4.5. I held the capital cost coefficient constant at its MLE, thereby admitting more certainty than actually exists. Despite this simplification the graphs below show the high degree of uncertainty around the intangible cost estimates. The probability distributions of intangible cost estimates for gasoline vehicles and hydrogen fuel cell vehicles assume 100% refuelling convenience for gasoline vehicles and 0% for HFCVs, and the same warranty coverage for both (5 years). Both probability distributions show that the most likely intangible cost estimate is only about 3% probable (circled regions on the graphs). In the case of gasoline vehicles, intangible costs can deviate from the most likely estimate by factors of 0.1 to 2. In this example, the most likely intangible benefit associated with gasoline vehicles is $74,000. However, the value of these benefits could range from about $7,400 to as much as $148,000. In the case of HFCVs, the graph the range of possible values is even greater. The most likely intangible benefit associated with HFCVs is about $60,000. But, these benefits could range from $500 to $116,000. Thus, the intangible costs of HFCVs relative to gasoline vehicles could also range widely.

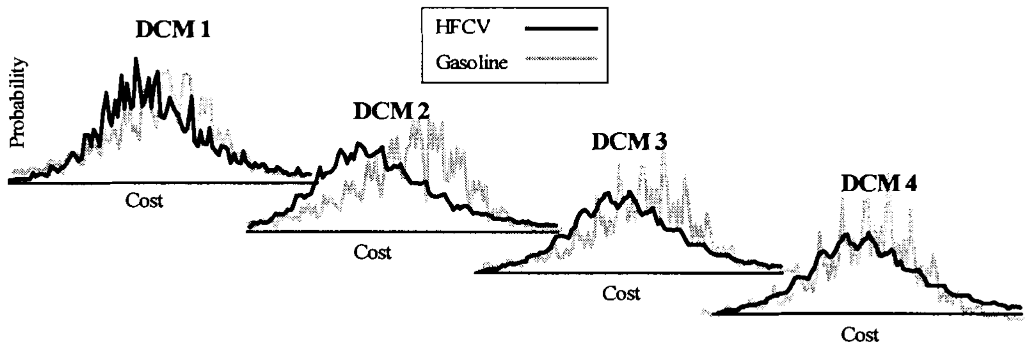
Figure 4.4: Uncertainty in intangible costs for gasoline and hydrogen fuel cell vehicles



For gasoline vehicles refuelling convenience = 100%. For HFCVs refuelling convenience = 0%. Warranty coverage for both technologies = 5 years.

Further, building the DIC requires at least two points, each estimated independently. In this way, the uncertainty introduced by each DCM is compounded in the DIC. Figure 4.5 illustrates this point. The probability distributions outlined in black correspond to HFCV costs and those in grey pertain to gasoline cars. Note that in estimating the parameters for the DIC I am assuming that this function represents how consumers' preference for hydrogen fuel cell vehicles change as a function of their increased market penetration, given a competition between gasoline cars and HFCVs. Thus, each data point for the DIC is the intangible cost attached to HFCVs relative to that of gasoline cars. Quantifying the joint uncertainty and propagating it through to the outputs from CIMS policy simulations is a formidable task in itself. Yet, the task is incomplete if we neglect to consider that a researcher's characterization of preference dynamics might not be representative of Canadian consumers' actual preferences, due to sampling biases discussed previously and possible limitations of experimental treatments. I consider that these sources of uncertainty are likely to be important, and warrant careful attention in future research.

Figure 4.5: Illustration of the uncertainty in the declining intangible cost function



Regardless of the confidence in the declining intangible cost function estimated for HFCVs, this function might have a relatively small influence on CIMS outputs by comparison with other functions and parameters already in CIMS. In particular, the choice of a progress ratio (PR) for the declining capital cost function is an important factor to assess, given that the initial capital costs for HFCVs effectively removes them from the competition and a favourable PR alone could increase the market share ratio of this technology during the simulation period. For this reason, along with propagating the uncertainty that I was able to quantify from my research through to CIMS outputs, I conducted a sensitivity analysis on the PR, which I explain in the next section.

The following DIC parameters resulted from matching the function defined in Equation 9 to the relative intangible costs for HFCVs estimated as the average values given by the DCMs for the four market share groups. As I explained previously, intangible costs estimated from the four DCMs did not show declining trends consistent with the expected influence of the "neighbour effect". That is, the intangible costs associated with HFCVs for respondents in market share group 1 were not always the highest among the four market share groups, nor were the intangible costs estimated for respondents in market share group 4 always the lowest. Still, I consider it important to show what might be reasonable estimates for the DIC function in CIMS, and in order to do this, I made two assumptions. First, instead of directly equating the intangible cost estimate from each DCM to its corresponding market share (in Equation 9), I used average values, and assumed that these values declined with increasing penetration of HFCVs. For example, Table 4.3 shows the intangible costs estimated from the four DCMs for a case in which refuelling convenience increases from 0% to 20% and warranty coverage stays constant at 5 years. At each value of refuelling convenience, I averaged the intangible costs derived from the four DCMs. I based the initial intangible costs (*Io* in Equation 9) on the average estimate for 0% refuelling convenience, and fitted the curve using the three other average values, assuming the market share ratios shown on Table 4.3.

Table 4.3: Example of assumptions for the DIC function

Model	Refuelling convenience (RC) 0%	5%	10%	20%
MS4 (20%)	$12,447	$9,202	$5,957	-$553
MS3 (10%)	$9,006	$6,477	$3,948	-$1,110
MS2 (5%)	$4,909	$2,454	$4	-$4,895
MS1 (0.03%)	$8,701	$6,059	$3,419	-$1,865
Average cost	**$8,766**	**$6,048**	**$3,332**	**-$2,106**
Note: warranty coverage (W) stays constant at 5 years.				

Market share HFCV	Intangible costs (RC = 0%, 5%, 10%, 20%; W = 5)
0.03%	$8,766
5%	$6,048
10%	$3,332
20%	-$2,106

Second, in cases where the attribute value is the same across the four market share groups, I assumed that intangible costs decline as a function of increased HFCV market shares. I based the difference in these costs among the four market share groups on the average difference. Table 4.4 shows the intangible cost estimates for HFCVs for a case in which refuelling convenience is 0% and warranty coverage is 5 years. I averaged the intangible costs derived from the four DCMs, at these attribute values, and set this average as the initial intangible cost (*Io* in Equation 9). To estimate the remaining three data points, I sequentially subtracted one-third of the average difference in intangible costs from the previous intangible cost, as shown on Table 4.4.[36] I used these values to fit the curve, assuming the same market share ratios as in the previous example.

[36] I used one third of the average difference instead of simply the average difference to err on the conservative side (i.e., leading to a lower rate of decline).

Table 4.4: Example #2 of assumptions for the DIC function

Model	Refuelling convenience = 0%
MS4 (20%)	$12,447
MS3 (10%)	$9,006
MS2 (5%)	$4,909
MS1 (0.03%)	$8,701
Average cost	**$8,766**
Average difference	$3,777
Average difference / 3	**$1,259**
Note: warranty coverage (W) stays constant at 5 years.	

Market share HFCV	Intangible costs (RC = 0%; W = 5)
0.03%	$8,766
5%	$7,507
10%	$6,248
20%	$4,989

Each combination of intangible costs required a re-estimation of DIC parameters. Table 4.5 shows the parameter combinations and assumptions about attribute values I used for the reference case and policy cases.[37] In the reference case, the intangible cost estimates correspond to a situation where there are no stations with proper fuel for HFCVs and that the warranty coverage is today's standard (5 years). "Incremental RC" is a case where refuelling convenience increases incrementally, but the warranty coverage remains at 5 years. "Constant RC" means that the intangible cost estimates from the DCMs assumed an input value of 20% for refuelling convenience. Warranty coverage remains at 5 years. Finally, "incremental RC and warranty programme"

[37] The CIMS transportation database already contained (static) intangible costs for the 10 vehicle types represented in the single-occupancy vehicle competition. Since the focus is on the competition between HFCVs and gasoline I only made alterations to data specific to HFCVs, but considered the pre-existing intangible costs for gasoline vehicles in fitting the DIC. More specifically, the database ascribes an intangible cost of $6,555 to high efficiency gasoline vehicles, which I added to the average intangible costs for HFCVs estimated from my models.

assumes the same input values for refuelling convenience as in the "incremental RC" case, but the intangible cost estimates are different because warranty coverage is extended to 8 years.

Table 4.5: Parameters for the declining intangible cost function

Case	Assumption	Io	A	k
Reference	RC = 0%; W = 5	$15,321	0.099122476	12.13492448
Incremental RC	RC =0%, 5%, 10%, 20%; W =5	$15,321	0.173754635	25.63275202
Constant RC	RC = 20%; W = 5	$4,449	0.239300028	16.64946911
Incremental RC and warranty programme	RC = 0%, 5%, 10%, 20%; W = 8	$12,779	0.19677429	30.66609368
RC = refuelling convenience; W = warranty coverage (years); Io = initial intangible cost; A and k define the shape of the curve and the rate of change				

4.3 Simulating Policies

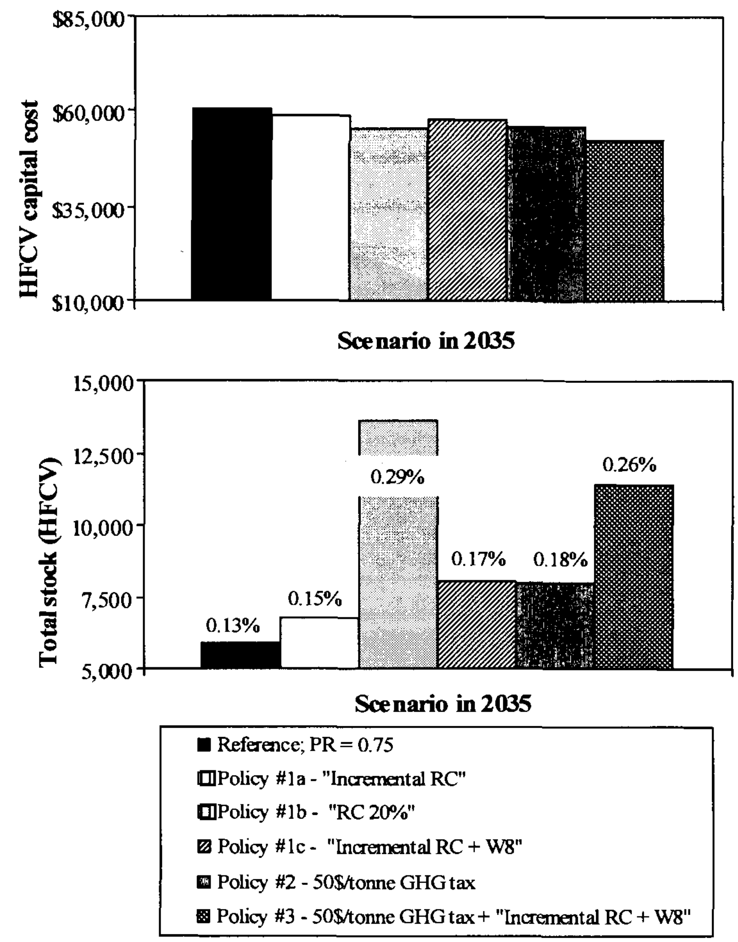
To illustrate CIMS' new potential to represent preference dynamics, I simulated four types of policies on the Ontario transportation sector. All simulations assume a progress ratio of 0.75. Although I cannot draw definitive conclusions from these simulation exercises, it is interesting to explore what causes the differences among modelling outputs. If we were confident in the representation of preference dynamics for HFCVs, we could extend the results of these simulations to the rest of the regions, as CIMS models transportation technology competition similarly across Canada. In terms of vehicle competition, regions only differ in their levels of base stock. Except for an emissions tax, which would apply to the economy in general, the simulated policies focus on accelerating the adoption of HFCVs. A brief description of these policies follows.

- *Policy set #1 - Incentives to accelerate the commercialization of hydrogen fuel cell vehicles.* These include subsidies targeting fuel infrastructure development and supporting increased warranty coverage on HFCVs. The first in this series of policies assumes infrastructure development in a phased fashion – refuelling convenience increases from 5% to 20% during the simulation period (Policy #1a - "Incremental RC"). The second assumes an increase in refuelling convenience to 20% (Policy #1b - "RC 20%"). The third combines phased-in infrastructure development with a warranty programme (Policy #1c - "Incremental RC + W8").
- *Policy #2 - A greenhouse gas (GHG) emissions tax.* The tax rate was set to $50/tonne of GHGs, which translates to a 12 cent / litre increase in gasoline prices (assuming a year 2000 average).
- *Policy #3 - A greenhouse gas (GHG) emissions tax plus incentives for the commercialization of HFCVs.* This policy combines Policy #2 (emissions tax) and Policy #1c (subsidies towards a phased-in infrastructure development and an extended warranty programme).
- *Policy #4 - Strict emissions restrictions plus incentives for the commercialization of HFCVs.* This policy modelling exercise is meant to simulate such sector specific market-oriented regulations as the vehicle emission standards in California, in conjunction with incentives specific to HFCVs. In this policy, the federal government implements strict emissions restrictions and works with vehicle manufacturers to introduce cost-competitive HFCVs in 2010. The acceleration in development results in a HFCV that is only 30% higher in capital and operating cost than the equivalent high efficiency gasoline vehicles. The policy design also includes subsidies aimed at

phasing in hydrogen refuelling infrastructure and an extended warranty programme. This is Policy #4.

Figure 4.6 shows the outcomes of the first three sets of policies for the year 2035. Figure 4.7 represents the outcomes of the fourth simulation exercise. Of the first three sets of policies, Policy #1b (refuelling convenience increased to 20%) achieves the greatest penetration of the target technology by 2035, surpassing the number of HFCVs in the reference case by about 7,761 (about 2.3 times greater than the reference case). This policy design results in a new market share of HFCVs relative to gasoline just under 1% (about 0.3% total market share ratio). The GHG tax plus incentives for HFCVs (Policy #3) achieves the second highest penetration of HFCVs, increasing the take-up of HFCVs by about 1.9 times compared to the reference case. Not surprisingly, the GHG tax (Policy #2) alone does little to improve the penetration of HFCVs, as new market shares are distributed among vehicle types with lower capital cost than HFCVs yet with better fuel efficiency than the average gasoline car. All sets of policies are effective in reducing single occupancy and increasing walking / cycling, transit, and high occupancy vehicle use compared to the reference case.

Figure 4.6: Results of policy simulations (#1 to #3)



"Incremental RC" = improved refuelling convenience from 0% to 20%; "RC 20%" = refuelling convenience set at 20%; W8 = extended warranty coverage (8 years)
Values in percentages listed above each column are the ratio of HFCVs to gasoline vehicles (total market share).

Regarding the evolution of capital costs for HFCV in the policy simulations, the following observations are worth noting. In the reference case, the capital cost declines from $139,988 in 2005 to $60,672 in 2035. In Policy #3, the capital cost is $52,884 in 2035. Policies #1a, #1b, #1c, and #2 bring the capital cost down to $58,746, $55,520, $57,680, and $56,061, respectively. Although the difference in magnitude among these deterministic outputs is relatively minor, these results could illustrate the importance of incorporating preference dynamics in the modelling exercise. Except for Policy #2 (the GHG tax), all policy cases have a different representation of preferences towards HFCVs than the reference case, and all cases assume the same progress ratio for the DCC. Thus, we can likely attribute differences in policy outcomes to the different representation of consumer preferences, allowing the analyst to test feedbacks between changes on the supply side (DCC) and changes in the way people make decisions regarding HFCVs (DIC).[38]

However, because Policies #1 to #3 all assume an extremely unfavourable initial capital cost for HFCVs, we see limited penetration of HFCVs over the reference case (producing only small reductions in GHG emissions), and we do not manage to reproduce more optimistic forecasts by other researchers for HFCV capital costs. For example, based on mass production assumptions and depending on the fuel pathway chosen, one study forecasts the cost differential between fuel cell vehicles and comparable gasoline cars to range between $2,000 and $7, 000 in 2020 (Greene and Plotkin 2001).

The results of simulating Policy #4 give a more accelerated view of the commercialization of HFCVs than the previous simulation exercises. The first graph in Figure 4.7 shows the total stock of HFCVs resulting from the policy imposing strict emissions restrictions combined with incentives for HFCVs (Policy #4). This figure also shows the evolution of the market share ratio (%) of HFCVs relative to gasoline vehicles

[38] "Representation of consumer preferences" in this context refers to differences in intangible costs for HFCVs resulting from variations in attribute values.

(see the secondary y-axis). Table 4.6 displays the total stocks of HFCVs resulting from the implementation of Policy #4 compared with the equivalent reference case.

Figure 4.7: Results of policy simulations (#4)

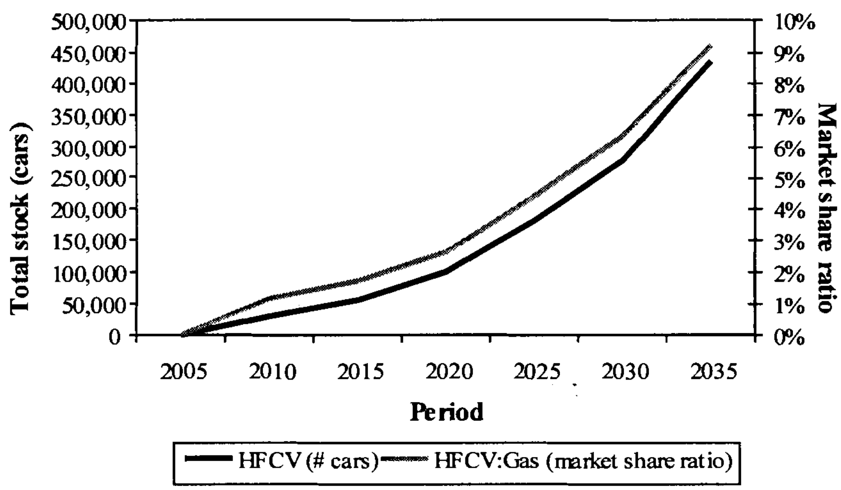


Table 4.6: Evolution of HFCV stocks under Policy #4

Case	2010	2015	2020	2025	2030	2035
Reference	332	522	823	1,519	2,939	5,870
Policy #4	30,205	57,150	100,774	180,433	276,817	435,049

Policy #4 successfully increases the adoption of HFCVs. Their market share relative to gasoline cars increases from 0% to 9% during the simulation period. In fact, the policy mix improves the competitive advantage of the target technology to such a degree that single occupancy vehicle use increases at the expense of walking and cycling, transit, and high occupancy vehicle use. The results of this policy run are probably on the optimistic end of the spectrum. In this case, the dynamic between the DIC and the DCC combine to reduce the capital cost of HFCVs from $31,872 to $18,915 during the simulation period. A further refinement to this type of policy modelling would be to have the capacity to (1) specify a minimum capital cost a given technology could drop to during the run, or (2) change the progress ratio (PR) once the emerging technology reached a certain production level. As an example of the latter case, Thomas et al. (1998) in their fuel cell vehicle forecasts switch from a PR of 0.819 to 0.93 when fuel cell production units surpass 300,000. This means that, prior to a cumulative production of 300,000, each doubling in production results in an 18% cost reduction. But, once cumulative production of fuel cell units exceeds the threshold quantity, each doubling in production reduces costs by only 7%. The sensitivity analyses below show the importance of this parameter in determining HFCV market shares.

To compare how these modelling exercises correspond to other scenarios for the future we can turn to the National Energy Board's (NEB's) characterizations of the composition of Canada's passenger vehicle sub-sector between 2000 and 2025 (Government of Canada 2003). "Canada's Energy Future" considers two scenarios, one in which gasoline vehicles continue to dominate the passenger vehicle fleet ("supply push"), and the other which assumes that Canadians become aware of the magnitude of the environmental costs associated with gasoline cars and are willing to pay for cleaner alternatives ("techno-vert"). Both scenarios focus on the competition among three vehicle types: gasoline internal combustion engine, hybrid gasoline-electric, and hydrogen fuel cell vehicles. In the "supply push" scenario HFCVs do not manage to penetrate the market at all. The reference case I present above shows a 0.04% market share for HFCVs relative to gasoline vehicles for 2025. Given the degree of uncertainty in my estimates, I consider the two results comparable. In contrast, HFCVs achieve about a 50% market share relative to gasoline cars in the NEB's "techno-vert" scenario, which is clearly optimistic in comparison to the results in Figure 4.7. Despite the crude nature of these comparisons, they are instructive in reinforcing the message that gasoline cars are likely to remain the dominant technology in the long-term in the absence of policy interventions.[39] These interventions could range from awareness campaigns, if we believe that information provision will be enough to incite a drastic and sustained change in consumer behaviour (as the "techno-vert" case assumes), to more forceful regulatory and fiscal policies.

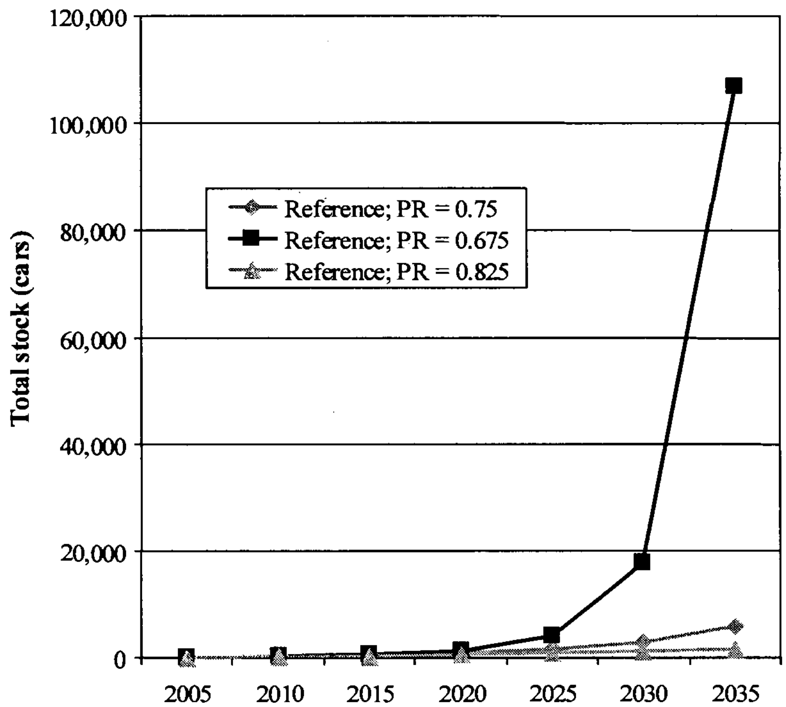
4.3.1 Sensitivity Analyses on CIMS parameters

To give an idea of the uncertainty introduced into CIMS' outputs through parameters in the declining capital cost function and the declining intangible cost function, I conducted a series of sensitivity analyses on the reference case used in the previous policy simulations. Figure 4.8 illustrates the changes in total stocks of HFCVs in the year 2035 that result by varying the progress ratio in the reference case (0.75) by 10%. Not surprisingly, a shift in PR to 0.675 causes a dramatic difference in the uptake of HFCVs by 2035, in comparison with the reference case and with a PR of 0.825. Recall that a PR of 0.675 means that each doubling in cumulative production decreases production costs by 32.5%; whereas, a PR of 0.825 reduces costs by 17.5% per doubling of cumulative production. In 2035, HFCV stock for a PR of 0.675 is 18.2 times greater than in the reference case, whereas a shift to a PR of 0.825 decreases the reference case vehicle stock by a factor of 0.72. Based on these analyses, I recommend that future exercises in policy modelling use a PR no greater than 0.75. That is, cost efficiencies per doubling of cumulative production should not exceed 25%. Also, to improve CIMS'

[39] A fair comparison of modelling outputs normalizes the basic economic assumptions underlying the modelling framework to a common standard.

portrayal of technological change the model should have the capacity to switch to a higher progress ratio once a threshold level of stock is attained during a run. Otherwise, the production efficiencies CIMS simulates are likely to be overly optimistic, specifically for technologies with very low levels of initial stock and very high capital costs.

Figure 4.8: Results for sensitivity analyses - progress ratio



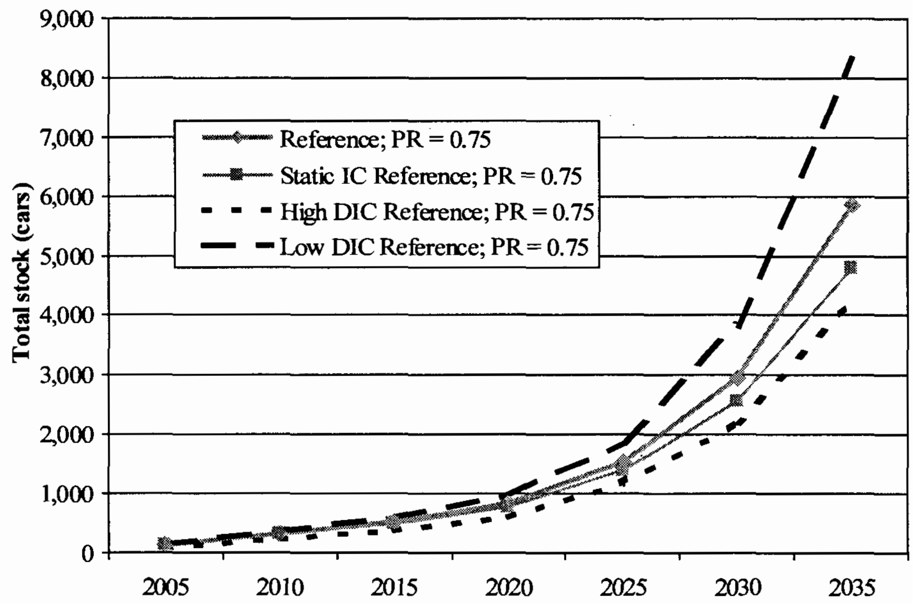
The second series of sensitivity analyses focuses on intangible costs. Here, I compare the reference case to the following scenarios: 1) a declining intangible cost function estimated with the highest intangible costs for HFCVs relative to gasoline cars from the discrete choice models (DCMs) for the four market share groups. These costs are two standard deviations to away from the most likely estimates for HFCVs and gasoline. I used averages to estimate the initial intangible cost and the difference among the four market share ratios. 2) A declining intangible cost function estimated with the lowest intangible costs for HFCVs relative to gasoline cars from the models for the four market share groups. These costs are two standard deviations away from the most likely estimates for HFCVs and gasoline. I used the same approach as in point 1. 3) A static representation of intangible costs, using the same initial intangible cost as the reference case, input into CIMS as a one-time cost. Table 4.7 shows the new DIC parameter estimates for scenarios 1 and 2. Although it is preferable to propagate uncertainty using a probabilistic representation, scenarios 1 and 2 are confidence intervals that show possible upper and lower ranges of CIMS outputs, informed by the uncertainty analyses in previous sections.

Table 4.7: Parameters for the DIC function - sensitivity analyses

Case	Assumption	Io	A	k
Sensitivity analysis - high intangible costs	RC = 0%; W = 5	$27,675	0.23271670	16.3707242
Sensitivity analysis - low intangible costs	RC = 0%; W = 5	$10,376	0.11969501	12.6599925
RC = refuelling convenience; W = warranty coverage (years); Io = initial intangible cost; A and k define the shape of the curve and the rate of change				

Two main observations emerge from this sensitivity analysis on the DIC. Compared to the progress ratio, differences in CIMS' outputs resulting from variations in intangible costs for HFCVs are likely to be more modest. In this analysis, the stock of HFCVs corresponding to the low dynamic intangible cost scenario is 1.4 times greater than in the reference case in 2035. For the same year, using high dynamic intangible costs or static intangible costs decreases the reference case vehicle stock by factors of 0.29 and 0.18, respectively. The other interesting observation is that the evolution of HFCV stocks using a static representation of consumer preferences is most similar to the case with high but dynamic intangible costs. This observation could point to the importance of modelling consumer preferences dynamically. In this example, a static intangible cost of $15,321 is similar to using intangible costs at the high end of the probability distributions to estimate the DIC function, in which the initial intangible cost is $27,675. In other words, using static intangible costs could underestimate the market penetration potential of emerging technologies in the long run.

Figure 4.9: Results for sensitivity analyses - intangible costs



CHAPTER 5 SUMMARY AND CONCLUSIONS

The general goal of this research was to improve the capacity of CIMS, a hybrid energy-economy simulation model, to simulate technological change in the long run. Specifically, the aim was to improve the behavioural parameters in CIMS to be able to capture how long-run preferences for unconventional technologies might be influenced by government policy. Previous work within the Energy and Materials Research Group (EMRG) has developed a methodology to use the results of discrete choice models to inform CIMS with behavioural parameters that describe decision-making in personal urban transportation, residential heating, and industrial steam generation. My research is an extension of these previous efforts, which assume a static representation of consumer preferences. My research focused on trying to understand the evolution of consumer preferences for hydrogen fuel cell vehicles (HFCVs), and translating this understanding to behavioural parameters in CIMS. The focus was on personal vehicle choice and on HFCVs specifically because of (1) the significance of personal greenhouse gas emissions from single occupancy vehicle use in Canada and (2) the potential for (environmental and social) change that the technology represents.

As I describe in the following discussion, trying to meet the research objectives was an adaptive process. In contrast to the companion study on preferences for hybrid electric vehicles (HEVs), the actual results from my study did not correspond to the results I had expected to achieve at the outset of the research. I suggest that the challenges I encountered related to the uncertainty around HFCVs, respondents' reactions to this uncertainty, and flaws in the experimental design. In any case, differences in results between the two studies offer interesting lessons to future researchers at EMRG. Section 5.1 is a summary of my research findings on consumer preferences for hydrogen fuel cell vehicles. Section 5.2 summarizes how I incorporated these preferences into CIMS and illustrate CIMS' new simulation potential. Finally, Section 5.3 discusses possible improvements to the experimental design to further our understanding of consumer preference dynamics for disruptive technologies, and recommends ways to improve CIMS' portrayal of decision-making in personal vehicle use.

5.1 Canadians' Preferences for Hydrogen Fuel Cell Vehicles

The experimental design for the survey in this research had two components (1) the use of a blocking variable and a technique called Information Acceleration (IA) to treat the global pool of respondents, and (2) a discrete choice experiment (DCE). The first component was designed to capture the "neighbour effect".[40] For this purpose, I randomly divided the global pool of respondents into four groups, and gave each group information corresponding to fictional market shares of HFCVs. The second component, the DCE, was identical across the four market share groups, and asked respondents to choose between a HFCV and a gasoline car based on a list of changing vehicle attributes. The survey was administered to an online panel of respondents recruited by a marketing firm. It is likely that the survey format and the sampling method introduced

[40] The hypothesis behind the "neighbour effect" is that people's value for hydrogen fuel cell vehicles (and hence, their propensity to choose them over gasoline cars) will change as the number of people owning this vehicle technology increases.

self-selection and coverage biases in the survey results. However, these biases were a necessary trade-off to attain the response quality and efficiency needed for this research.

I used the survey responses from the four market share groups to estimate a series of multinomial logit (MNL) models, some of which included personal characteristics and stated attitudes as explanatory variables. I found that stated attitudes about the adoption of new technologies could help predict the propensity for choosing HFCVs over gasoline vehicle. Since my objective was to understand the preferences of average Canadian urban car drivers, I removed the potential attitudinal bias by filtering the innovators and laggards from the four data sets. I estimated separate MNL models for the respondents categorized as (early) majority in each of the four market share groups. Also, I estimated a single model for all innovators and one for all laggards. With the exception of fuel cost, all attribute coefficients are statistically significant at the 95% level and have the appropriate sign across the six MNL models. This means that the attributes included in the choice experiment were relevant to decision-making. The resulting models also show that (1) all else being equal, consumers value HFCVs much more than gasoline vehicles, as indicated by the alternative specific constant (ASC); (2) capital cost, refuelling convenience, and government subsidy are the most important vehicle attributes in choosing between a gasoline car and an HFCV; and (3) consumers value a one-dollar increase in government subsidy about twice to three times as much as a dollar decrease in capital cost – innovators, in particular, highly value government subsidies.

Although validating market share forecasts from the MNL models to observed market conditions is not possible, one finding common to all MNL models is noteworthy. Market share forecasts are dominated by the constant specific to hydrogen fuel cell vehicles (the ASC). In other words, the models predict a significant penetration of HFCVs, even under conditions unfavourable to this technology. For example, models predict that HFCVs can capture a 12% to 24% market share relative to gasoline vehicles even in the absence of stations with proper fuel for HFCVs. Previous research has identified several possible reasons for the dominance of the ASC. The two most common reasons are (1) the discrepancy between stated preferences and respondents' revealed behaviour, and (2) the omission of attributes that are important to decision-making in the choice experiment. However, both reasons could apply to Mau's (2004) almost identical study on hybrid electric vehicle preferences, and he did not find the same dominance. I suggest that the dominant appeal of HFCVs relative to gasoline vehicles relates to the radically new features of HFCVs. People might be attracted to the radical newness of this vehicle type – the disruptive drive train, the fly-by-wire technology, for example. Perhaps people like the status this vehicle technology would confer. At the same time, people's lack of familiarity with HFCVs could have led them to assume that the potential negative attributes were negligible, whereas in the companion study respondents might have had some information on the negative attributes associated with hybrid electric vehicles.

Regardless of the dominance of the ASC in model forecasts, I found interesting differences in response to changes in attributes among the three categories of technology adoption (innovators, majority, and laggards). Representatives of the majority are more responsive to changes in vehicle capital costs and refuelling convenience than the other two groups. This means that the adoption of hydrogen fuel cell vehicles in Canada is heavily dependent on manufacturers and policymakers being able to substantially reduce the upfront costs faced by the consumer and increase the fuelling infrastructure. Changes in the levels of government subsidy are more significant to innovators and the majority than to laggards. Changes in warranty coverage have more of an effect on the adoption rate of laggards and the majority than on innovators.

I further assessed the robustness of my models by (1) testing whether the vehicle attributes in the choice experiment had non-linear effects on utility, and (2) quantifying the uncertainty in parameter estimates for the six models. These analyses confirmed that some attributes have a non-linear effect on utility, and the effect of these differ among the three categories of technology adoption. The results helped me to select the range of attribute values in calculating the intangible costs for HFCVs relative to gasoline vehicles. The results of the uncertainty analyses showed that the parameter estimates from my models are considerably less certain than those in Horne's (2003) vehicle choice study, but closely match the uncertainty in the results of Mau's (2004) HEV study.

The assumption in the experimental design was that the treatment of the four market share groups would influence people's response to the choice experiment through the "neighbour effect". The expectation was that people in market share group 1, who received information about a world where HFCVs captured 0.03% of the gasoline vehicle market, would value HFCVs less than those in market share group 2, where HFCVs capture 5% of the gasoline vehicle market. In turn, people in market share group 2 would value HFCVs less than those in market share group 3, where HFCVs attain 10% of the gasoline vehicle market. Finally, people in market share group 4 would value HFCVs the most, corresponding to the fictional HFCV penetration of 20%. However, market share forecasts do not differ significantly among the four majority models, neither do the differences in the relative intangible costs associated with HFCVs follow the declining trend I had anticipated. Despite the lack of empirical evidence for the "neighbour effect", given the experimental design in this research, I consider that the results from my models provide usable "ball park" values. The next section summarizes the approach I took and the assumptions I made in order to incorporate preference dynamics for HFCVs in CIMS. The remaining discussion is restricted to the four majority discrete choice models.

5.2 Simulating Preference Dynamics in CIMS

Using the methods previously developed by EMRG researchers, I translated the results of one of my discrete choice models (market share group 3 - MS3) into two static behavioural parameters for use in CIMS (1) the private discount rate for new vehicle choices and (2) the heterogeneity in this market. I chose to fit CIMS to the MS3 discrete choice model because this DCM yielded the most conservative (highest) estimates for the discount rate, which, I assumed, would be appropriate for investment decisions about unknown technologies. In case this assumption was wrong, I verified that the solution for market heterogeneity could equally apply to discrete choice models that gave lower discount rates. My point estimate for market heterogeneity is almost twice as high as the estimates for new vehicle choice in Horne (2003) and Mau (2004). A low value for market heterogeneity means that even technologies with high costs can capture a portion of the new market share. Therefore, using Horne's and Mau's estimates for market heterogeneity in CIMS would allow technologies with higher costs to penetrate the market more significantly than if we were to use my estimate, all else being equal. This could mean that consumers make investment decisions differently for disruptive vehicle technologies than for conventional or evolutionary technologies. The uncertainty in my estimates for the private discount rate and market heterogeneity is large, and I caution readers to consider this factor in drawing any conclusions.

I estimated the intangible costs of hydrogen fuel cell vehicles relative to gasoline vehicles by comparing the coefficient estimates for intangible attributes (refuelling convenience, warranty coverage, and the alternative specific constant) to the coefficients for capital cost from my four (majority) DCMs. I expected to see a declining trend in intangible costs from MS1 to MS4, but I did not. Instead, I observed a consistent v-shaped pattern, over a wide range of plausible values for refuelling convenience and warranty coverage. In contrast, Mau (unpublished manuscript) did find the expected trend in intangible costs for hybrid electric vehicles relative to gasoline vehicles. This difference in outcomes led to my conclusion that the experimental treatment did not achieve the intended effect in my study for reasons specific to hydrogen fuel cell vehicles (disruptive technologies). I propose three explanations to account for the differences in preference dynamics in our two studies. First, I suggest that the choice task was too demanding for respondents, triggering the use of simplified heuristics in decision-making rather than explicitly trading off attribute values. These simplifications in the choice experiment could have applied equally across the four market share groups, giving importance to the blocking variable. Second, expectations about the fuelling infrastructure, corresponding to the hypothetical market scenarios depicted during the Information Acceleration part of the survey, could have confounded the effect of the blocking variable with respondents' utilities for refuelling convenience.[41] Third, adopting a disruptive technology could require that the technology reach some threshold level of development, convenience, or consumer acceptance. My conclusion is that the blocking variable was not strong enough to overcome the effect of these three factors (and possibly others) on respondents' choices.

Despite the variance in expected outcomes, I remain convinced that "the neighbour effect" is likely to influence consumers' purchasing decisions about HFCVs. For this reason, and because very little information exists about the long-term adoption potential of HFCVs in Canada, I decided to use the results from my models to estimate parameters for the declining intangible cost function (DIC) anyway. I could not directly match the intangible cost estimates from my four DCMs to the DIC curve equation. Instead, I used average intangible costs calculated from the four discrete choice models for given values for refuelling convenience and warranty coverage, which I assumed to correspond to the four adoption levels of HFCVs in the experiment (0.03%, 5%, 10%, 20%). In cases where I had to set the magnitude of the differences in intangible costs among assumed adoption levels, I based it on average differences from the DCMs. By changing the values for refuelling convenience and warranty coverage, new average intangible costs were estimated, corresponding to a series of DIC parameters in CIMS. In this way, I was able to use CIMS to simulate policies specific to hydrogen fuel cell vehicles that change the intangible cost for this technology during the simulation period. I illustrated CIMS' new potential to incorporate preference dynamics by simulating

[41] I tested whether removing refuelling convenience as an explanatory variable in estimating DCMs resulted in the expected trends in intangible costs. Although this DCM specification attenuates the dominance of the alternative specific constant in market share forecasts, the v-shaped pattern in intangible costs remains.

policy mixes that increased the fuelling infrastructure for hydrogen fuel cell vehicles and introduced extended warranty programmes for this vehicle type. I explored the uncertainty in the DIC function by doing a series of sensitivity analyses on this function and the declining capital cost function. I found that the choice of progress ratio is likely to have more influence on CIMS' outputs (stock of hydrogen fuel cell vehicles) than variations in intangible costs. However, the influence of the DCC would be lessened in cases where initial technology stocks were higher and initial capital costs were lower than current values for HFCVs in CIMS' database. I also found that using a static representation of consumer preferences could result in similar outcomes as using a dynamic representation estimated from average intangible costs at the high end of the range. In other words, the assumption of static consumer preferences could overvalue the intangible costs consumers actually perceive, and underestimate their propensity to switch to new technologies in the long run.

5.3 Recommendations for Future Modelling Efforts

Previous EMRG researchers identified the need to incorporate preference dynamics into CIMS, in order to improve the simulation model's capacity to depict decision-making over the long term, and to provide a useful tool for policymakers to assess their role in major technology transformations for sustainable policymaking. My research responds to this recommendation. As I described above, my research was not without challenges. These challenges led me to use my empirical results as a basis for the estimation of declining intangible cost functions for HFCVs. Thus, I have low confidence in the realism of these declining intangible cost functions and consider my results as approximations. Despite the uncertainty in my results, a survey of current literature indicates that very few researchers and energy-economy modellers have successfully addressed preference dynamics for emerging technologies. And, in the case of (hydrogen) fuel cell vehicles, commercial deployment of this technology is not expected to take place until 2010 or 2020 (Greene and Plotkin 2001, Weiss et al. 2000, and Azar et al. 2000) - even with stringent carbon constraints (Azar et al. 2000). Therefore, my research addresses two issues that are inherently uncertain, for which very little information useful to policymakers exists. As long as policymakers and other users are aware of the range of uncertainty in CIMS' outputs, we can use the declining intangible cost functions estimated for hydrogen fuel cell vehicles in competition with gasoline vehicles from my research to explore how governments can assist in transforming the market for hydrogen fuel cell vehicles. In the following discussion I provide recommendations for future research in behaviourally realistic hybrid modelling. I divide these recommendations into three topics (1) improving the experimental design to capture preference dynamics for disruptive vehicle technologies; (2) continuing to use stated preferences; and (3) making improvements in CIMS to ensure consistency and transparency in the way it models new car competition.

5.3.1 Capturing Preference Dynamics

If EMRG were to continue to study preference dynamics using a similar approach to Mau's (unpublished manuscript) and mine, I would recommend the following changes to the experimental design: (1) ensure that the blocking variable is significant to respondents and is not confounded by attributes in the choice experiment; (2) consider whether different attitudes towards new technologies in the survey sample might influence the results; (3) use a type of discrete choice model that allows for correlation among alternatives in the choice experiment; and (4) specify the DCM formulation to account for non-linearities in parameters. The first point seems obvious to me now, but was not apparent prior to analyzing the data. As mentioned previously, I suggest that the blocking variable in my research did not achieve the desired effect, because other factors had a stronger influence on respondents' value for hydrogen fuel cell vehicles. These factors pertained to the four market share groups. Future studies on disruptive technologies might consider blocking survey groups using a more tangible and familiar market condition than the relative proportion of people driving the alternative technology. For example, if I were to re-design my study, I would use a measure of refuelling infrastructure as the blocking variable. In the choice experiment, I would substitute refuelling convenience for some measure of car size, such as cargo space.

In a given survey sample, it is likely that respondents will have different attitudes towards new technologies. This is not an issue if we want to estimate aggregate market share forecasts of new technologies from DCMs, because these differences in attitudes exist in the population at large. However, differences in attitudes do matter if the goal is to estimate behavioural parameters in CIMS. It matters because these parameters result from comparisons among DCM coefficients. For example, as my research indicates, innovators and laggards value capital cost and refuelling convenience differently, hence, the intangible cost for a given technology for these two groups differ as well. Future work in EMRG might consider ways to screen out respondents whose attitudes about new technologies might deviate from the mainstream.

The third issue that became apparent in analyzing the data was that, in uncertain situations, people are likely to use heuristics to make decisions. For example, they might focus on a single attribute to choose among options, or they might apply elimination rules. The use of these mental simplifications can imply that respondents' choices in the experiment are correlated, which calls into question the appropriateness of using the multinomial logit (MNL) model. This type of random utility model assumes that the unobserved or random portion of utility (ε_j in Equation 2) is of equal variance and independent among alternatives. But, if we violate these model assumptions and respecifying the model fails to capture the correlation within the observed portion of utility (V_j in Equation 2), a different model assumption is needed. Other model assumptions, such as the general extreme value, the probit, and the mixed logit models are more flexible but are also more complex (Train 2003). Despite the added complexity, future studies should consider using a more flexible type of discrete choice model, in order to achieve a better representation of consumer preferences.

The discrete choice models I used to estimate a series of declining intangible cost functions assume linear and additive relationships of attributes in the utility function. However, the analyses I performed on the results of my DCMs revealed that certain attributes have non-linear effects on utility. Specifying the DCMs to account for any non-linearities is important for the estimation of behavioural parameters in CIMS. In this study, I identified that non-linearities existed but did not respecify the functional form of the DCMs, this could be an extension in future studies.

5.3.2 Using Stated Preferences

Throughout this paper I have emphasized the uncertainty in the results of my DCMs, which propagates through to the parameters estimated in CIMS and to outputs in the policy simulation exercises. Because of the uncertainty involved in capturing stated preferences for emerging technologies and the substantial financial costs of collecting stated preference data, EMRG research should consider using other data sources. If financial costs of data collection are a concern, expert opinion, literature surveys, or meta-analysis might provide a satisfactory indication of intangible costs and private discount rates for emerging technologies. Taking this approach might increase the breadth of technologies that EMRG researchers can cover. If the objective is to reduce the uncertainty in DCM coefficients, building DCMs that combine revealed and stated preference data has the potential to capture complex behavioural characteristics (Hensher et al. 1999).

Models estimated from joint stated and revealed preference data sources tend to outperform models estimated from revealed preferences (Adamowicz et al. 1997) or stated preferences (Brownstone et al. 2000) alone. Specifically, revealed preference data provides important information on the scale of the model, existing attributes, and alternative specific constants, whereas stated preference data is crucial for describing preferences for attributes outside the market arena (Brownstone et al. 2000). However, there are several issues to consider in combining preference data, and the methods involved can be quite demanding. For a start, using combined preference data precludes the use of the MNL model specification, which tends to be too restrictive to allow for the combination of different data sources (Hensher et al. 1999, Brownstone et al., 2000). In any case, research of this type would likely require guidance from experts in random utility modelling.

5.3.3 Ensuring Consistency and Transparency in CIMS

The focus of my research was to portray the evolution of the competition between hydrogen fuel cell vehicles and gasoline vehicles. I did this by estimating a series of declining intangible cost functions in CIMS that exclusively applied to hydrogen fuel cell vehicles relative to high efficiency gasoline vehicles. Thus, the policy simulations in this research are not actually representative of the current or potential vehicle market. A more comprehensive analysis would include a dynamic representation of consumer preferences and / or supply-side efficiencies for all vehicle technologies in CIMS – perhaps even conventional gasoline cars.[42] Because the results of my study are very specific to fuel cell vehicles, extending these results to other disruptive technologies, such as battery electric vehicles, might not be appropriate. Thus, I suggest that EMRG continue to try to understand consumer preference dynamics, but in a way that is inclusive of vehicle types with the potential to change the characteristics of Canada's urban vehicle fleet. Although the recent focus on the personal urban transportation sector is warranted, EMRG should explore preference dynamics in other types of decisions.

Finally, the sensitivity analyses on the policy simulations in this research showed that small changes in the progress ratio of CIMS' declining capital cost function led to

[42] Macauley et al. (2002) emphasize the importance of including technological advances in defending technologies in modelling competitions among technologies. The most obvious way CIMS can incorporate advances in defending technologies (e.g., light-weighting in conventional gasoline vehicles) is by activating the declining capital cost function. As well, consumers' preferences for these defending technologies can change in response to technological advances.

more significant variations in hydrogen fuel cell vehicle stocks than changes in the parameters of the declining intangible cost function. This is because the initial capital cost of hydrogen fuel cell vehicles in CIMS' database is very high, and initial production levels are very low. These two factors represent considerable opportunities for supply-side efficiencies. However, the potential for learning-by-doing in the case of this vehicle technology would decrease as the technology matures. As other engineering assessments have done (see Thomas et al. 1998), I suggest adding a feature in CIMS that allows the user to change the progress ratio during a simulation once the emerging technology attains a certain production level.

I base my previous recommendations on the assumption that policymakers are interested in reducing the uncertainty in forecasts as much as possible. As I have explained, several sources of uncertainty are pervasive in behaviourally-realistic hybrid modelling – particularly when the modelling exercise involves technologies under research and development. Thus, we might not be able to recognize the benefits of efforts aimed at reducing these uncertainties, yet the costs are likely to be high. My final recommendations are that EMRG (1) evaluate the expected value of obtaining "perfect information" for selected technology competitions in CIMS, (2) take stock of the preference data acquired to date and ensure that results have been incorporated into the working version of CIMS, and (3) systematically update the technology data in CIMS' database.

APPENDICES

Appendix A

Description of Survey Design for 3^6 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

0 0 0 0 0 0
0 1 1 2 1 1
0 2 2 1 2 2
1 0 1 1 1 2
1 1 2 0 2 0
1 2 0 2 0 1
2 0 2 2 1 0
2 1 0 1 2 1
2 2 1 0 0 2
0 0 2 1 0 1
0 1 0 0 1 2
0 2 1 2 2 0
1 0 0 2 2 2
1 1 1 1 0 0
1 2 2 0 1 1
2 0 1 0 2 1
2 1 2 2 0 2
2 2 0 1 1 0

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 HFCV c c2 d d2 e e2 f f3	Gasoline Car a a2 b b2 Alternative Fuel Car c c3 d d1 e e3 f f1	Gasoline Car a a3 b b2 HFCV c c3 d d3 e e1 f f3
Gasoline Car a a3 b b3 Alternative Fuel Car c c2 d d1 e e1 f f3	Gasoline Car a a1 b b1 Alternative Fuel Car c c1 d d1 e e1 f f1	Gasoline Car a a2 b b3 Alternative Fuel Car c c1 d d3 e e1 f f2

Gasoline Car a a1 b b2 Alternative Fuel Car c c2 d d3 e e2 f f2	Gasoline Car a a1 b b2 Alternative Fuel Car c c1 d d1 e e2 f f3	Gasoline Car a a1 b b3 Alternative Fuel Car c c2 d d3 e e3 f f1
Gasoline Car a a2 b b1 Alternative Fuel Car c c1 d d3 e e3 f f3	Gasoline Car a a2 b b2 Alternative Fuel Car c c2 d d2 e e1 f f1	Gasoline Car a a3 b b3 Alternative Fuel Car c c1 d d2 e e2 f f1
Gasoline Car a a1 b b1 Alternative Fuel Car c c3 d d2 e e1 f f2	Gasoline Car a a3 b b1 Alternative Fuel Car c c2 d d1 e e3 f f2	Gasoline Car a a3 b b1 Alternative Fuel Car c c3 d d3 e e2 f f1
Gasoline Car a a3 b b2 Alternative Fuel Car c c1 d d2 e e3 f f2	Gasoline Car a a2 b b3 Alternative Fuel Car c c3 d d1 e e2 f f2	Gasoline Car a a1 b b3 Alternative Fuel Car c c3 d d2 e e3 f f3

Appendix B

Urban Transportation 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.

Urban Transportation Survey

3% Complete

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? One

2. What is the body type of the vehicle you most often use? Small/Compact Car

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

Make:	Model:	Year:
Toyota	Camery	1999
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.

5 years, 1 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.

2 years, 0 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.*
$16000

8. On average, how much do you pay to maintain this vehicle every year, not including fuel costs?
Please use your best estimate. $1000

9. On average, what are the fuel costs for this vehicle? $ 40 dollars per week

10. On average, how far can you drive on a full tank of gas ? 400 Kilometers 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.* 6

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	○	○	●	○
Magazines or other publications: Reading Consumer Reports, Automotive news, etc	○	●	○	○
Word of mouth: Talking to your family, friends, and acquaintances	○	○	●	○
Your own past experience	●	○	○	○
Other information sources that you might go to when considering to buy a new vehicle. Please specify: Internet Research	○	○	○	●

Next >>

Urban Transportation Survey

9% Complete

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Section 2: Knowledge of Hydrogen Fuel Cell Vehicles

What is your current state of knowledge regarding hydrogen fuel cell vehicles?
Please check all statements that apply to you.

☐ I keep up to date with developments regarding this technology.

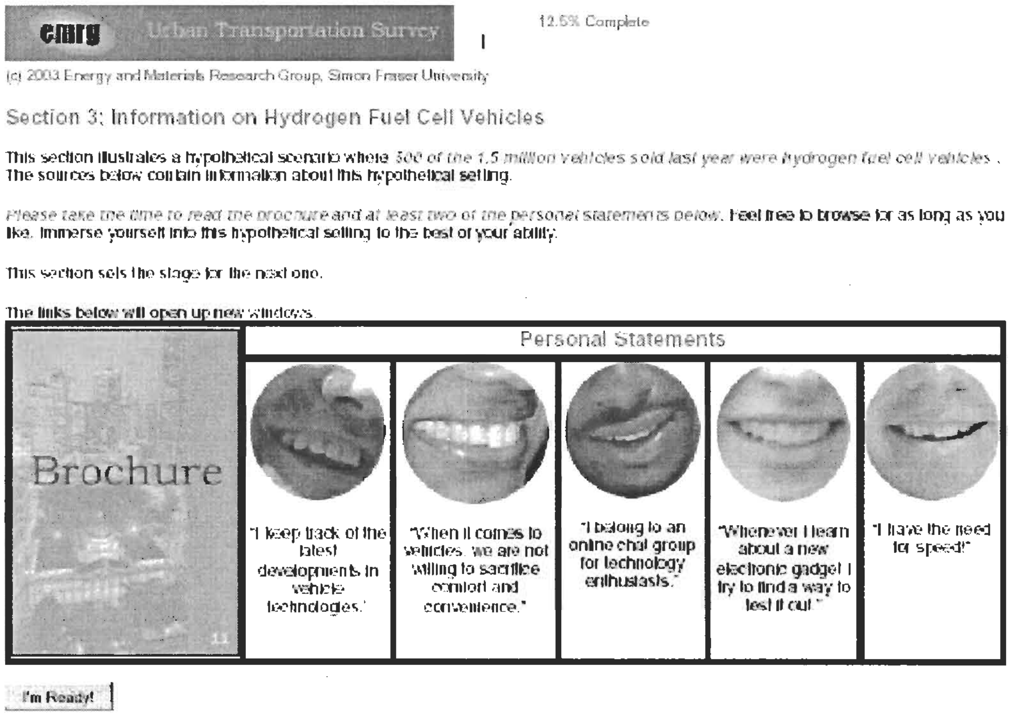
☐ I have read articles about this technology in newspapers and/or magazines.

☐ I have heard about this technology on the radio and/or television.

☐ I have heard about this technology from friends and/or acquaintances.

☑ I am unfamiliar with this technology.

Next >>



emrg Urban Transportation Survey

12.5% Complete

(c) 2003 Energy and Materials Research Group, Simon Fraser University

Section 3: Information on Hydrogen Fuel Cell Vehicles

This section illustrates a hypothetical scenario where *300 of the 1.5 million vehicles sold last year were hydrogen fuel cell 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.

Brochure

Personal Statements

"I keep track of the latest developments in vehicle technologies."

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

"I belong to an online chat group for technology enthusiasts."

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

"I have the need for speed!"

I'm Ready!

Brochure for Hydrogen Fuel Cell Vehicles

Safe, reliable, clean, affordable to service, and with a range comparable to conventional vehicles it's no wonder 500 of the 1.5 million vehicles sold last year were hydrogen fuel cell vehicles.

Breaking away from the conventional internal combustion engine has never been so easy. Hydrogen fuel cell vehicles look something like this: no engine, no steering column, no need for gasoline, and no harmful exhaust. They have all the performance of conventional vehicles while running much, much cleaner.

PERFORMANCE Powered by a revolutionary technology hydrogen fuel cell vehicles provide faster acceleration and quieter operation than conventional vehicles.

Instead of running on an internal combustion engine, these vehicles create power through the reaction of hydrogen and oxygen in a fuel cell. The reaction produces electricity, necessary to run the electric motor that drives the wheels, and water vapour - the reaction's only tailpipe emission.

Steering and braking in hydrogen fuel cell vehicles are fully electronic, using techniques pioneered in fly-by-wire aircraft cockpits. This provides opportunities to enhance both ride and handling; yet another improvement over conventional vehicles.

STYLING Hydrogen fuel cell vehicles' "running gear" - **the fuel cell** stack, electronic controls, and **electric motors - is** all inside the chassis. This **innovative architecture** has opened up new opportunities to devote more space to passengers and cargo.

CONVENIENCE AND SAFETY Hydrogen refueling stations are becoming more available in **cities across Canada**. Look for one in your

neighbourhood. More and more Canadians are driving hydrogen fuel cell vehicles. Do you know why? Visit your local dealership, go for a test drive, and find out!

(Close this window to go back to the survey)

Close Window

emrg Urban Transportation 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 hydrogen fuel cell vehicle .

I've had the vehicle for a few months now, and I enjoy its fast acceleration and silent operation. This vehicle technology is truly revolutionary: no engine, no steering column, no need for gasoline, and only water vapour as exhaust. Plus, I get about the same mileage as I did with my previous gasoline vehicle, and I have a lot more passenger and cargo space.

Although I can only fuel up in dedicated service stations, the benefits of this new technology make up for the minor inconvenience. I'm really excited about being one in five thousand Canadians driving this type of vehicle!

(Close this window to go back to the survey)

Close Window

emrg Urban Transportation Survey

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 hydrogen fuel cell 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, although there are more hydrogen refueling stations now than there were a few years ago we still would have to go out of our way to find a proper service station to fuel the car. 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 hydrogen fuel cell vehicle doesn't even have an engine everything's electronic!

We know that hydrogen fuel cell 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.

(Close this window to go back to the survey)

Close Window

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I belong to an online chat group for technology enthusiasts.

I bought a hydrogen fuel cell vehicle two months ago. So far, I am enjoying the ride. The car is great in terms of performance and reliability. What thrilled me most about this vehicle was the departure from the conventional internal combustion engine. Powered by a stack of fuel cells, my new vehicle has no engine, no steering column, and only emits water vapour as exhaust. Electronic braking and steering are a great improvement over the mechanical system in gasoline vehicles. I feel like I'm flying a plane! Fueling is a bit of an issue, but that will change as more people buy this technology. And I'm sure this will happen.

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 hydrogen fuel cell vehicles. I'm happy about being among the first 450 Canadians to switch to this technology!

(Close this window to go back to the survey)

Close Window

emrg Urban Transportation Survey

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

When I found out about the hydrogen fuel cell 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. I mean "normal" in terms of performance and handling, but this technology is very far from what we call "normal". Instead of an internal combustion engine, hydrogen fuel cell vehicles are powered by a stack of fuel cells - the vehicle has no engine, no steering column, a lot more passenger space, and no smelly exhaust. Braking and steering are electronic: driving is like flying a plane.

I'm told that you need to fuel up with hydrogen as often as you would with a normal gasoline car. I guess that would be one disadvantage; hydrogen fueling stations are few and far between. But this will change as more people buy this type of vehicle technology. And I'm sure this will happen.

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!

(Close this window to go back to the survey)

Close Window

emrg Urban Transportation Survey

I have the need for speed!

I went and bought a hydrogen fuel cell 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 sweeeet 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!

(Close this window to go back to the survey)

Close Window

emrg Urban Transportation Survey

17% Complete

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

emrg Urban Transportation Survey

19% Complete

Section 4: Your Vehicle Choices

17 more comparisons to go...

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

	Gasoline Vehicle	Hydrogen Fuel Cell Vehicle
Purchase Price (Does not include government taxes or subsidies)	**$17600**	**$27200**
Fuel Cost / Week	**$44**	**$40**
Warranty Coverage Period (Includes power train and batteries)	**5 years or 100,000 Km (60,000 Miles)**	**10 years or 163,000 Km (100,000 Miles) / 10 ans ou 163,000 Km (100,000 Miles)**
Stations with Proper Fuel	**All Stations**	**1 in 20 / 1 sur 20 (The right fuel is available only in zones with the highest traffic volume) / (Le bon carburant est uniquement offert dans les zones de la ville où le trafic est le plus intense)**
Subsidy on Purchase Price (The subsidy is given by the Canadian Government 6 months after purchasing the vehicle as a rebate)	**No Subsidy**	**$1600**
I would choose this vehicle:	○	○

Next >>

emrg Urban Transportation Survey

89% Complete

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.).

A. Volkswagon Jetta

B. ford Mustang

C. Toyota echo

Submit

emrg Urban Transportation Survey

89.5% Complete

(c) 2003 Energy and Materials Research Group, Simon Fraser University

Section 5: Views on Vehicle Preferences (Continued)

1. Assume that you or your family has decided to purchase a Volkswagon Jetta, and the Volkswagon is available as a hydrogen fuel cell vehicle and as a conventional gasoline vehicle.

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

- (●) Gasoline vehicle, or ( ) hydrogen fuel cell vehicle

2. Assume that you or your family has decided to purchase a ford Mustang, and the ford Mustang is available as a hydrogen fuel cell vehicle and as a conventional gasoline vehicle.

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

- (●) Gasoline vehicle, or ( ) hydrogen fuel cell vehicle

3. Assume that you or your family has decided to purchase a Toyota echo, and the Toyota echo is av as a hydrogen fuel cell vehicle and as a conventional gasoline vehicle.

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

- (●) Gasoline vehicle, or ( ) hydrogen fuel cell vehicle?

4. If you or your family has decided to buy a hydrogen fuel cell vehicle, but the vehicle is not available Volkswagon Jetta, ford Mustang, or Toyota echo, how likely are you to consider other makes and mod

Very Likely	Likely	Unlikely	Very Unlikely
( )	( )	(●)	( )

Next >>

Urban Transportation Survey

93% Complete

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.

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

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	●	○
Full-Size Car	○	●
Truck	○	●
SUV	○	●
Mini-Van	○	●

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 *hydrogen fuel cell vehicle* **to replace your primary vehicle.**

Unfortunately, you have found out that hydrogen fuel cell 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	●	○
Full-Size Car	○	●
Truck	○	●
SUV	○	●
Mini-Van	○	●

7. Assume that when it comes time to replace your primary vehicle, 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 emission vehicles, such as hybrid-electric, hydrogen fuel cell, natural gas vehicles, etc.

Assume that at this time, you have decided to purchase a conventional gasoline car to replace your primary vehicle.

What is one-time lump sum in Canadian dollars that you would be willing to pay to obtain this permit, so you could keep driving a gasoline vehicle?

$ 10000

What is one-time lump sum in Canadian dollars that you would be willing to pay to obtain a permit for a second gasoline vehicle?

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

What is one-time lump sum in Canadian dollars that you would be willing to pay to obtain a permit for a third gasoline 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.
○	●	○

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.	●	○	○
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.	●	○	○

Next >>

EMRG Urban Transportation Survey

96.5% Complete

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? 26-30

What is your family annual income? $20,000 or less

What is your household size? 1

In which region of Canada are you located? British Columbia

What is your gender? Female

What is your highest level of education completed? University

logout >>

Appendix C

Profiles of Early Adopters and Early Majority used to construct fictional word-of-mouth statements. Adapted from Moore (1999) and Bolton (1999).

Market Share Scenario 2: Early Adopters	
Value for blocking variable	Characteristics of reference people
• Number of hydrogen fuel cell passenger vehicles (HFCVs) is 83,000 • HFCVs represent 5% of new market share in Canada relative to conventional gasoline cars	• "Early adopters" are attracted to products with unique features and applications but the product must have a new benefit. • They are visionaries and perceive themselves as "agents of change", which means that they do not rely on well-established references to adopt a technology and tolerate imperfections in the new technology.

Market Share Scenario 3: Early Majority	
• Number of hydrogen fuel cell passenger vehicles (HFCVs) is 143,000 • HFCVs represent 10% of new market share in Canada relative to conventional gasoline cars	• People in the "Early Majority" adopt a new technology based on the expectation that it represents a productivity improvement over the incumbent technology. • They like continuity and evolution rather than revolution. • They will not purchase a new technology without good references, but are willing to learn how to use the new technology if required.

Market Share Scenario 4: Early Majority (stage 2)	
• Number of hydrogen fuel cell passenger vehicles (HFCVs) is 249,000 • HFCVs represent 20% of new market share in Canada relative to conventional gasoline cars	• Successful and sustained penetration of the new technology is contingent on it becoming increasingly user friendly. • People in this sub-segment (and in Late Majority) wait until an industry standard is on the market and expect a lot of technical support.

Appendix D

Scripts for Telephone Recruiting and Pre-Screening

English Version

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 one dollar 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 over19 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?

1. Yes
2. No THANK AND TERMINATE WITH REJECTION REASON 5

Part E - 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.

Part F - 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 at least once a week 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.

French Version

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 vehicule

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")

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 addresse de courriel?
   1- Oui
   2- Non (Merci. Terminer le questionnaire avec "Rejet Raison 5")

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 électronique 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 trés 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 intérêssé(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 desolé(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 desolé(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 E

Demographic characteristics of respondents	MS1 (N_{total} = 250) (N_{demo} = 236)	MS2 (N_{total} = 252) (N_{demo} = 236)	MS3 (N_{total} = 258) (N_{demo} = 244)	MS4 (N_{total} = 259) (N_{demo} = 241)	All MS (N_{total} = 1019) (N_{demo} = 957)
Age of respondent					
20 or below	0.4	0.0	2.0	1.2	0.9
21-25	2.5	4.7	2.5	3.7	3.3
26-30	10.2	8.1	11.1	8.7	9.5
31-35	13.1	11.0	9.8	10.4	11.1
36-40	15.7	14.8	14.3	16.2	15.3
41-50	31.8	30.5	26.6	31.1	30.0
51-60	17.8	22.9	25.0	23.2	22.3
Over 60	8.5	8.1	8.6	5.4	7.6
Household income					
$20,000 or less	3.0	3.8	8.2	5.8	5.2
$21,000 to $40,000	27.5	23.3	18.9	18.3	21.9
$41,000 to $60,000	20.3	25.0	20.9	19.1	21.3
$61,000 to $80,000	18.2	22.0	20.9	23.2	21.1
$81,000 to $100,000	11.9	8.9	12.3	14.9	12.0
$101,000 and above	14.8	14.4	16.0	13.7	14.7
No answer	4.2	2.5	2.9	5.0	3.7
Region					
Atlantic	7.6	8.9	7.8	8.7	8.3
QC	23.7	23.3	20.5	24.1	22.9
ON	36.9	37.7	41.4	35.7	37.9
Prairies	15.3	16.9	17.2	19.1	17.1
BC	16.5	12.7	12.7	12.4	13.6
No answer	0.0	0.4	0.4	0.0	0.2
Gender of respondent					
Male	30.5	36.9	34.8	35.7	34.5
Female	69.1	63.1	65.2	64.3	65.4
No answer	0.4	0.0	0.0	0.0	0.1
Education of respondent					
Grade 9 or less	1.3	1.3	0.8	0.4	0.9
High school	20.3	30.1	19.7	23.7	23.4
College	39.8	35.2	42.2	35.7	38.2
University	38.6	33.5	37.3	39.8	37.3
No answer	0.0	0.0	0.0	0.4	0.1

All values in percentages. N_{total} = the total number of respondents; N_{demo} = the number of respondents that provided demographic information

Appendix F

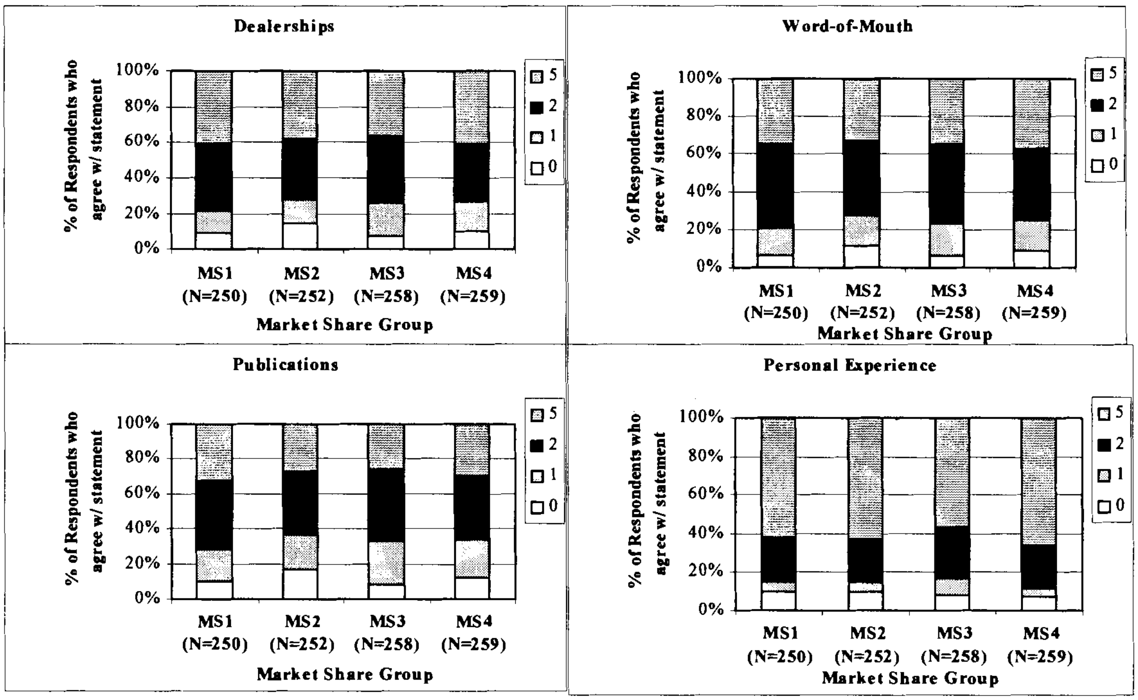
Question to gain insight into key influences in people's decisions regarding vehicle purchases

(From Section 1: Characteristics of Your Current Vehicle)

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.

Dealerships: Talking to experts and going for test drives
Magazines or other publications: Reading Consumer Reports, Automotive News, etc.
Word-of-mouth: Talking to your family, friends, and acquaintances
Your own past experience

1 = Not at all important
2 = Somewhat important
5 = Very important
0 = Don't know or does not apply

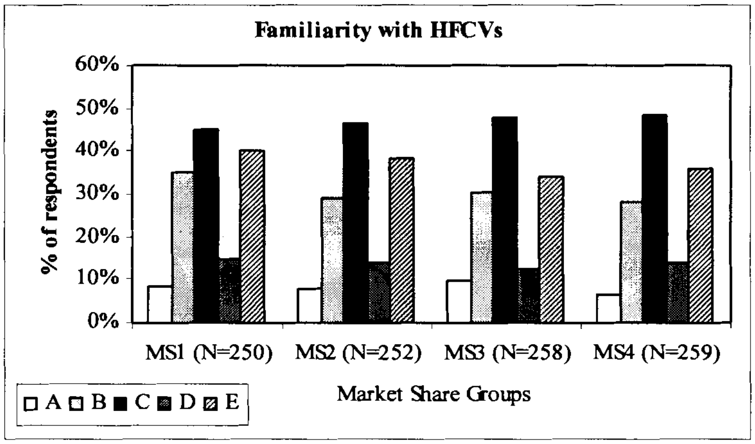


Question to elicit respondents' general awareness of hydrogen fuel cell vehicles (HFCVs)

(From Section 2: Knowledge of Hydrogen Fuel Cell Vehicles)

What is your current state of knowledge regarding hydrogen fuel cell vehicles? Please check all statements that apply to you.

A = I keep up to date with developments regarding this technology.
B = I have read articles about this technology in newspapers and/or magazines.
C = I have heard about this technology on the radio and/or television.
D = I have heard about this technology from friends and/or acquaintances.
E = I am unfamiliar with this technology[43].



Question to categorize respondents (albeit crudely) into points along technology adoption lifecycle.

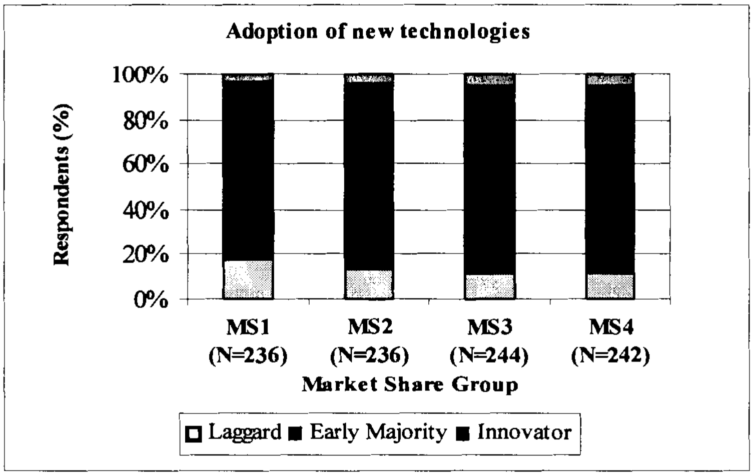
(From Section 6: Views on New Technologies)

Please indicate your views on purchasing new technologies. "New technologies" include items such as mobile phones (cellular phones), DVD players, alternative fuel vehicles, etc. Please check the statement that best describes your case.

- I would buy the new technology when most people have made the switch and it becomes inconvenient to own the old technology. (If respondent checks this statement they are classified as "laggard".)
- I would buy the new technology when it has proved itself and maintaining it is not problematic. (If respondent checks this statement they are classified as "early majority".)

[43] Here, "unfamiliar" could mean that the respondent has never heard of hydrogen fuel cell vehicles or that the respondent has *some* knowledge of hydrogen fuel cell vehicles but might not understand engineering aspects of the technology, for example. The statement was ambiguous to prevent respondents from reacting negatively to a statement implying complete ignorance of the vehicle technology (e.g., "I have never heard of hydrogen fuel cell vehicles").

- I want to be the first person in my neighbourhood, in my family, or among my circle of friends to buy the new technology. (If respondent checks this statement they are classified as "innovator".)



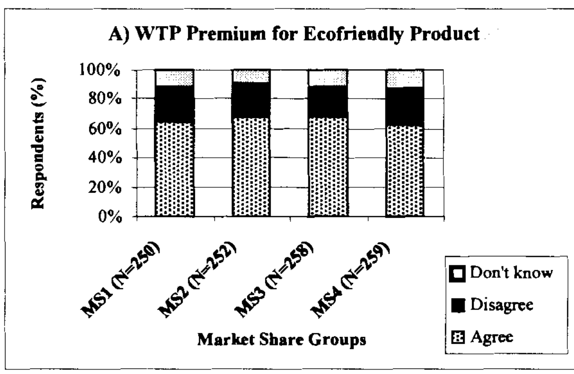
Question to assess people's willingness to pay a premium for a product with public good aspect.

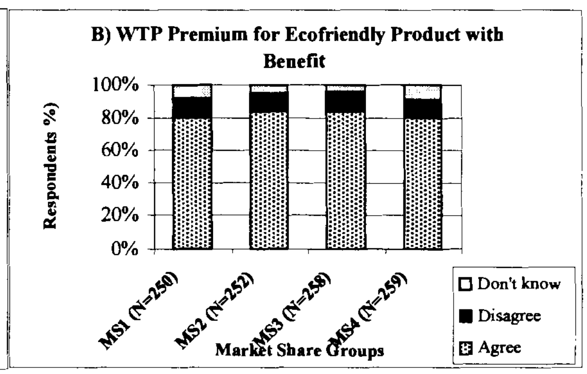
(From Section 6: Views on New Technologies)

Please indicate if you agree/disagree with the following statements, or if you don't know or the statements don't apply to you.

A) I would be willing to spend a bit more money to buy a technology that is ecologically friendly.

B) 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.





Question to assess people's loyalty to vehicle body types

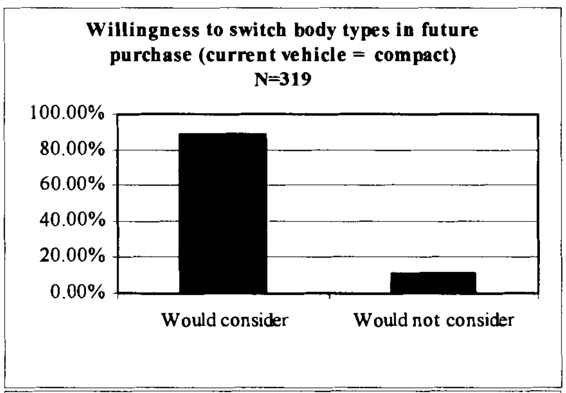
(From Section 5: Views on Vehicle Preferences)

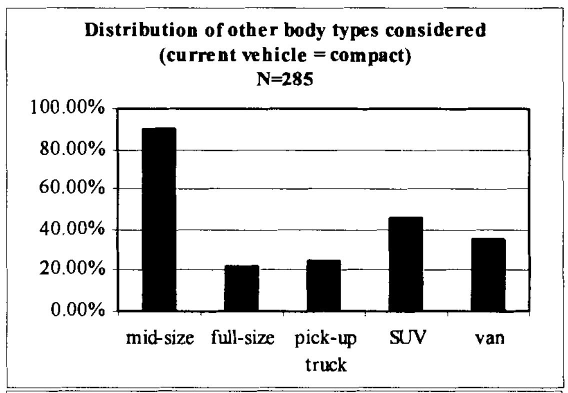
Assume that your primary vehicle has reached the end of its life. You and your family are now considering buying a new vehicle that will serve the same purpose (for example, if you use your primary vehicle to go to work, this new vehicle will also be used to take you to work). You and your family have decided to buy a hydrogen fuel cell vehicle to replace your primary vehicle. Unfortunately, you have found out that hydrogen fuel cell vehicles are not available in the body type of the vehicle you are replacing.

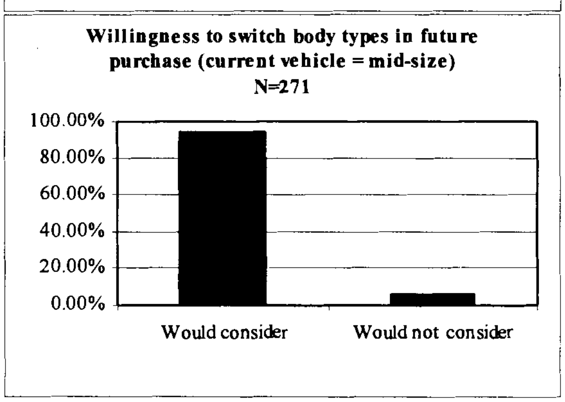
Please indicate if you would consider switching to the following (check all that apply):

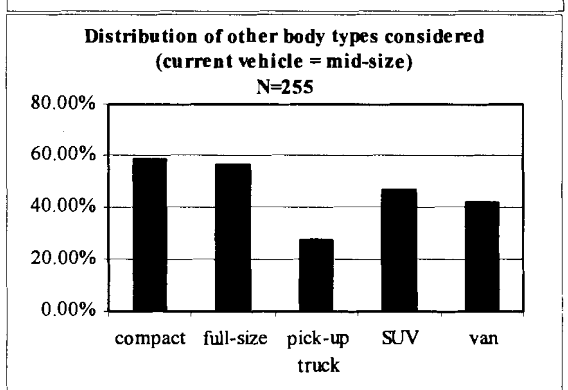
Compact Car
Mid-Size Car
Full-Size Car
Truck
SUV
Mini-Van

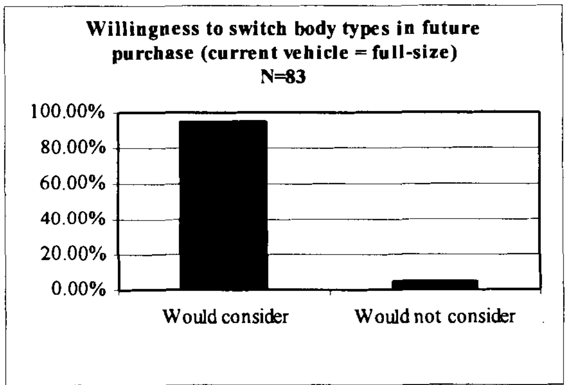
(Note: the respondent's current vehicle body type would not appear on the list of options.)

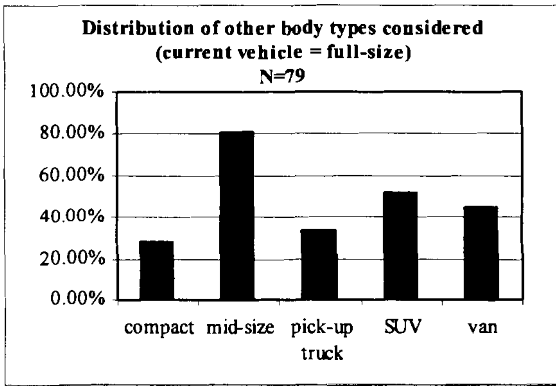


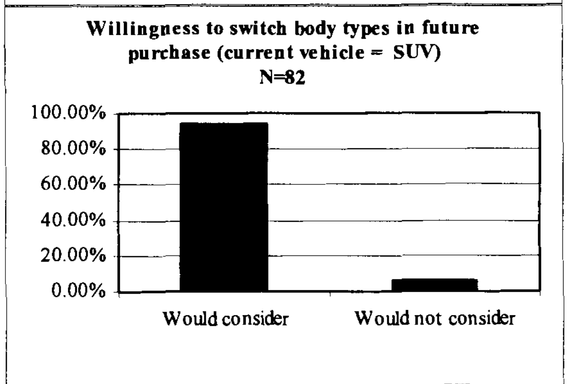


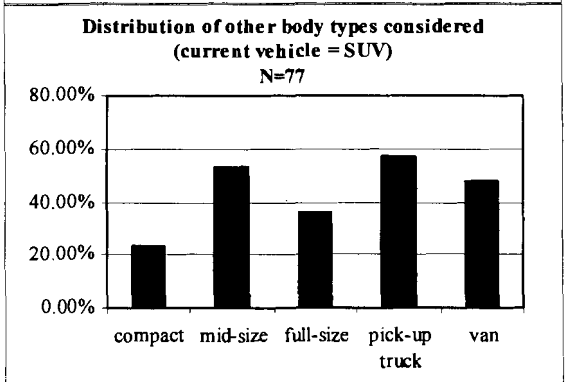


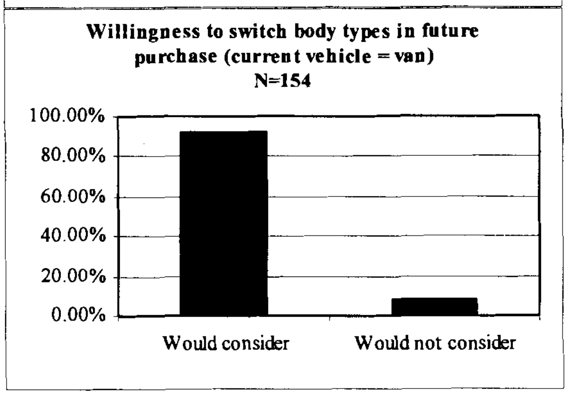


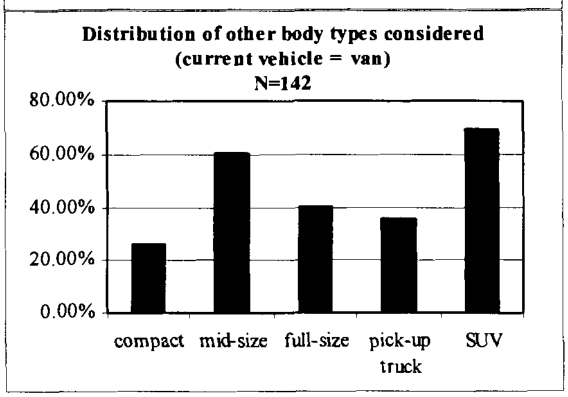

Willingness to switch body types in future purchase (current vehicle = full-size)
N=83
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
Would consider
Would not consider


Distribution of other body types considered (current vehicle = full-size)
N=79
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
compact
mid-size
pick-up truck
SUV
van


Willingness to switch body types in future purchase (current vehicle = SUV)
N=82
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
Would consider
Would not consider


Distribution of other body types considered (current vehicle = SUV)
N=77
80.00%
60.00%
40.00%
20.00%
0.00%
compact
mid-size
full-size
pick-up truck
van


Willingness to switch body types in future purchase (current vehicle = van)
N=154
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
Would consider
Would not consider


Distribution of other body types considered (current vehicle = van)
N=142
80.00%
60.00%
40.00%
20.00%
0.00%
compact
mid-size
full-size
pick-up truck
SUV

Appendix G

Results for the Basic Model with Respondent Characteristics

The initial model specification included the following personal characteristics:

- Income group (Y), where income groups were entered as mid-points: 10 000, 17 500, 22 500, 27 500, 32 500, 37 500, 45 000, 55 000, 65 000, 72 000, 87 500, and 100 000.
- Home region, ATL (Atlantic provinces), PRA (Prairie provinces), QC (Quebec), ON (Ontario) and BC (British Columbia).
- Respondents' willingness to pay a premium for ecologically-friendly technologies, yes (YEC) or no (NEC)
- Respondents' willingness to pay a premium for ecologically-friendly technologies that provide personal benefit, yes (YOW) or no (NOW).
- Whether the respondent was categorized as an innovator (INN), laggard (LAG) or early majority (EMA).

Because of collinearities among explanatory variables I was not able to estimate MNL models with all the personal attributes at the same time. So, I estimated two kinds of models for each market share group, one containing the home region and the other with income (8 models in total).

Basic Model with Respondent Characteristics (Region) Market Share 1 (Nobs = 4500)				
	Base Model		Reduced Model	
Attributes	β parameter	t-ratio	β parameter	t-ratio
CC	-0.000162	-19.7*	-0.00016	-19.6236
FC	-0.022706	-2.54273*	-0.02548	-2.88334
SUB	0.000314	11.6477*	0.000315	11.7617
RC	10.1767	16.3903*	10.0951	16.336
W	0.154537	8.15445*	0.153564	8.12206
HASC	8.81567	15.2795*	8.16585	14.7204
HxEMA	-0.472231	-1.66248		
HxLAG	-1.09488	-3.64952*	-0.70777	-6.19052
HxINN	-0.873606	-2.77692*	-0.45198	-2.20309
HxYOW	-0.534468	-3.26896*	-0.51346	-5.17009
HxNOW	-0.358527	-1.74625		
HxYEC	1.41234	9.10312*	1.33395	14.3827
HxNEC	-0.001747	-0.00978		
HxON	-0.827718	-4.15645*	-0.73319	-8.34932
HxATL	-1.37152	-5.3742*	-1.27706	-7.09769
HxPRA	-0.048933	-0.23427		
HxBC	-0.204242	-0.97076		
HxQC	-0.219749	-1.08809		
Log likelihood – full model			(base) -2082.79	(reduced) -2095.56
Log likelihood – constants only			-2711.47	-2711.47
Log likelihood – no coefficients			-3119.16	-3119.16

*Parameter is significant with 95% confidence. CC = vehicle purchase price; FC = fuel cost; SUB = government subsidy; RC = refueling convenience; W = warranty coverage, HASC = hydrogen fuel cell vehicle alternative specific constant; HxZ = interaction term between HASC and personal attribute.

Basic Model with Respondent Characteristics (Region) Market Share 2 (Nobs = 4536)				
	Base Model		Reduced Model	
Attributes	*ß* parameter	t-ratio	*ß* parameter	t-ratio
CC	-0.00019	-21.5645*	-0.00019	-21.6268
FC	-0.01464	-2.01546*	-0.01381	-1.92069
SUB	0.000291	10.0324*	0.000292	10.0912
RC	8.91073	15.039*	8.88992	15.0233
W	0.117277	6.58243*	0.116886	6.56734
HASC	7.58703	13.8404*	7.56992	13.8291
HxEMA	-0.763	-2.48054*	-0.6415	-3.85122
HxLAG	-1.65243	-5.08623*	-1.53832	-7.80484
HxINN	-0.71256	-2.07601*	-0.66303	-2.79943
HxYOW	-0.01517	-0.07956		
HxNOW	-0.11124	-0.48411		
HxYEC	0.945754	6.48372*	1.02884	11.6464
HxNEC	-0.12553	-0.7358		
HxON	0.275465	1.32061		
HxATL	-0.05994	-0.25067		
HxPRA	0.313266	1.40769		
HxBC	0.918559	4.07784*	0.68032	5.94676
HxQC	0.830525	3.89618*	0.61377	6.78196
Log likelihood - full model			(base) - 2256.03	(reduced) -2260.25
Log likelihood - constants only			-2889.99	-2889.99
Log likelihood - no coefficients			-3144.11	-3144.11
*Parameter is significant with 95% confidence. CC = vehicle purchase price; FC = fuel cost; SUB = government subsidy; RC = refueling convenience; W = warranty coverage, HASC = hydrogen fuel cell vehicle alternative specific constant; HxZ = interaction term between HASC and personal attribute.				

Basic Model with Respondent Characteristics (Region) Market Share 3 (Nobs = 4644)				
	Base Model		Reduced Model	
Attributes	ß parameter	t-ratio	ß parameter	t-ratio
CC	-1.85E-04	-21.66*	-1.86E-04	-21.82
FC	-3.23E-02	-4.08*	-3.12E-02	-3.99
SUB	4.00E-04	14.20*	3.94E-04	14.11
RC	9.13E+00	15.37*	9.07E+00	15.33
W	1.58E-01	8.61*	1.57E-01	8.59
HASC	6.82E+00	12.38*	6.71E+00	12.75
HxEMA	-3.73E-01	-1.16		
HxLAG	4.99E-02	0.15		
HxINN	8.81E-01	2.50*	1.18E+00	7.09
HxYOW	2.10E-01	1.14		
HxNOW	5.65E-02	0.27		
HxYEC	6.18E-01	4.80*	7.37E-01	8.96
HxNEC	-2.48E-01	-1.60		
HxON	1.97E-01	0.97		
HxATL	4.14E-01	1.73		
HxPRA	9.33E-02	0.43		
HxBC	6.33E-02	0.29		
HxQC	8.67E-01	4.11*	6.61E-01	7.12
Log likelihood - full model			(base) -2222.07	(reduced) -2233.01
Log likelihood - constants only			-2831.58	-2831.58
Log likelihood - no coefficients			-3218.97	-3218.97

*Parameter is significant with 95% confidence. CC = vehicle purchase price; FC = fuel cost; SUB = government subsidy; RC = refueling convenience; W = warranty coverage, HASC = hydrogen fuel cell vehicle alternative specific constant; HxZ = interaction term between HASC and personal attribute.

Basic Model with Respondent Characteristics (Region) Market Share 4 (Nobs = 4662)				
	Base Model		Reduced Model	
Attributes	β parameter	t-ratio	β parameter	t-ratio
CC	-1.39E-04	-18.22*	-1.38E-04	-18.30
FC	-1.39E-03	-0.16		
SUB	3.01E-04	11.60*	2.97E-04	11.57
RC	9.35E+00	15.53*	9.31E+00	15.51
W	1.63E-01	8.83*	1.63E-01	8.82
HASC	7.02E+00	12.78*	6.77E+00	12.65
HxEMA	-5.68E-01	-1.86		
HxLAG	-1.41E+00	-4.31*	-9.30E-01	-6.09
HxINN	-4.19E-01	-1.26		
HxYOW	3.94E-01	2.59*	4.51E-01	4.27E-06
HxNOW	-2.45E-01	-1.18		
HxYEC	8.21E-01	6.24*	6.38E-01	8.47E-09
HxNEC	-7.17E-01	-4.48*	-9.11E-01	4.00E-11
HxON	6.40E-01	2.96*	4.01E-01	1.09E-06
HxATL	5.93E-01	2.45*	3.72E-01	0.006717
HxPRA	-3.03E-02	-0.13		
HxBC	2.79E-01	1.15		
HxQC	3.59E-01	1.63		
Log likelihood - full model			(base) -2190.98	(reduced) -2199.33
Log likelihood - constants only			-2782.69	-2782.69
Log likelihood - no coefficients			-3231.45	-3231.45

*Parameter is significant with 95% confidence. CC = vehicle purchase price; FC = fuel cost; SUB = government subsidy; RC = refueling convenience; W = warranty coverage, HASC = hydrogen fuel cell vehicle alternative specific constant; HxZ = interaction term between HASC and personal attribute.

Basic Model with Respondent Characteristics (Income) Market Share 1 (Nobs = 4248)				
	Base Model		Reduced Model	
Attributes	ß parameter	t-ratio	ß parameter	t-ratio
CC	-1.74E-04	-18.37*	-1.74E-04	-18.40
FC	-3.56E-02	-3.57*	-3.60E-02	-3.61
SUB	3.21E-04	10.62*	3.21E-04	10.63
RC	1.02E+01	15.43*	1.02E+01	15.43
W	1.59E-01	7.87*	1.59E-01	7.87
HASC	8.37E+00	13.08*	8.17E+00	13.70
HxEMA	-9.93E-02	-0.43		
HxLAG	-6.86E-01	-2.75*	-6.00E-01	-5.14
HxYOW	-5.39E-01	-3.18*	-5.20E-01	-4.60
HxNOW	-4.99E-02	-0.23		
HxYEC	1.34E+00	8.65*	1.43E+00	14.37
HxNEC	-1.31E-01	-0.73		
HxY	-6.65E-06	-4.16*	-6.67E-06	-4.18
Log likelihood - full model			(base) -1844.08	(reduced) -1844.66
Log likelihood - constants only			-2399.27	-2399.27
Log likelihood - no coefficients			-2794.76	-2794.76

*Parameter is significant with 95% confidence. CC = vehicle purchase price; FC = fuel cost; SUB = government subsidy; RC = refueling convenience; W = warranty coverage, HASC = hydrogen fuel cell vehicle alternative specific constant; HxZ = interaction term between HASC and personal attribute.

Basic Model with Respondent Characteristics (Income) Market Share 2 (Nobs = 4248)				
	Base Model		Reduced Model	
Attributes	ß parameter	t-ratio	ß parameter	t-ratio
CC	-2.05E-04	-20.95*	-2.06E-04	-21.06
FC	-1.24E-02	-1.64		
SUB	3.26E-04	10.35*	3.27E-04	10.45
RC	9.27E+00	14.73*	9.27E+00	14.71
W	1.17E-01	6.21*	1.15E-01	6.13
HASC	7.74E+00	12.52*	7.97E+00	13.99
HxEMA	1.88E-01	0.98		
HxLAG	-7.41E-01	-3.29*	-9.61E-01	-7.42
HxYOW	1.57E-01	0.82		
HxNOW	1.62E-01	0.70		
HxYEC	9.37E-01	6.46*	1.08E+00	12.08
HxNEC	-2.11E-01	-1.23		
HxY	-7.22E-06	-4.70*	-7.04E-06	-4.63
Log likelihood – full model			(base) -2009.34	(reduced) -2012.02
Log likelihood – constants only			-2613.76	-2613.76
Log likelihood – no coefficients			-2832.19	-2832.19

*Parameter is significant with 95% confidence. CC = vehicle purchase price; FC = fuel cost; SUB = government subsidy; RC = refueling convenience; W = warranty coverage, HASC = hydrogen fuel cell vehicle alternative specific constant; HxZ = interaction term between HASC and personal attribute.

Basic Model with Respondent Characteristics (Income) Market Share 3 (Nobs = 4392)				
	Base Model		**Reduced Model**	
Attributes	**ß parameter**	**t-ratio**	**ß parameter**	**t-ratio**
CC	-1.84E-04	-20.39*	-1.84E-04	-20.42
FC	-2.96E-02	-3.71*	-2.94E-02	-3.70
SUB	3.92E-04	12.96*	3.92E-04	12.97
RC	8.88E+00	14.39*	8.87E+00	14.38
W	1.61E-01	8.48*	1.61E-01	8.47
HASC	8.33E+00	13.34*	8.31E+00	13.97
HxEMA	-1.49E+00	-8.31*	-1.48E+00	-8.31
HxLAG	-1.11E+00	-5.38*	-1.14E+00	-5.58
HxYOW	1.25E-01	0.65		
HxNOW	-2.66E-02	-0.12		
HxYEC	5.60E-01	4.24*	6.76E-01	7.67
HxNEC	-1.59E-01	-1.01		
HxY	-3.28E-06	-2.26*	-3.16E-06	-2.20
Log likelihood - full model			(base) -2046.56	(reduced) -2048.11
Log likelihood - constants only			-2576.85	-2576.85
Log likelihood - no coefficients			-2894.58	-2894.58

*Parameter is significant with 95% confidence. CC = vehicle purchase price; FC = fuel cost; SUB = government subsidy; RC = refueling convenience; W = warranty coverage, HASC = hydrogen fuel cell vehicle alternative specific constant; HxZ = interaction term between HASC and personal attribute.

Basic Model with Respondent Characteristics (Income) Market Share 4 (Nobs = 4338)				
	Base Model		Reduced Model	
Attributes	ß parameter	t-ratio	ß parameter	t-ratio
CC	-1.38E-04	-16.87*	-1.38E-04	-16.87
FC	4.62E-04	0.05		
SUB	3.08E-04	11.02*	3.08E-04	11.07
RC	9.93E+00	15.57*	9.93E+00	15.57
W	1.73E-01	8.87*	1.73E-01	8.88
HASC	7.60E+00	12.39*	7.41E+00	12.75
HxEMA	-1.76E-01	-1.00		
HxLAG	-1.13E+00	-4.94*	-9.64E-01	-6.15
HxYOW	5.09E-01	3.34*	5.44E-01	4.98
HxNOW	-8.51E-02	-0.41		
HxYEC	7.98E-01	5.92*	7.92E-01	5.97
HxNEC	-7.78E-01	-4.74*	-8.00E-01	-5.04
HxY	-3.12E-06	-2.14*	-3.28E-06	-2.27
Log likelihood - full model			(base) -1962.56	(reduced) -1963.09
Log likelihood - constants only			-2510.14	-2510.14
Log likelihood - no coefficients			-2882.10	-2882.10

*Parameter is significant with 95% confidence. CC = vehicle purchase price; FC = fuel cost; SUB = government subsidy; RC = refueling convenience; W = warranty coverage, HASC = hydrogen fuel cell vehicle alternative specific constant; HxZ = interaction term between HASC and personal attribute, representing the effect of Z personal attribute on respondents' utility for hydrogen fuel cell vehicles.

Results for the Chow Test Model

Chow Test Model (Nobs=18,342)				
	Base Model		Reduced Model	
Attributes	ß parameter	t-ratio	ß parameter	t-ratio
CC	-1.47E-04	-18.95*	-1.38E-04	-29.18
FC	-1.99E-02	-2.38*	-1.89E-02	-4.95
SUB	2.88E-04	11.40*	2.69E-04	18.30
RC	8.66E+00	29.12*	8.66E+00	30.32
W	1.38E-01	7.73*	1.34E-01	15.30
HASC	6.97E+00	27.47*	6.96E+00	27.46
CCMS2	-3.71E-05	-3.23*	-4.71E-05	-5.85
FCMS2	3.71E-03	0.34		
SUBMS2	-2.44E-05	-0.65		
RCMS2	-6.84E-01	-5.12*	-6.09E-01	-7.63
WMS2	-2.98E-02	-1.21		
CCMS3	-2.90E-05	-2.58*	-2.83E-05	-3.53
FCMS3	-8.09E-03	-0.72		
SUBMS3	8.65E-05	2.33*	1.20E-04	3.98
RCMS3	-5.83E-02	-0.42		
WMS3	1.07E-02	0.43		
CCMS4	2.24E-05	2.13		
FCMS4	9.43E-03	0.81		
SUBMS4	-2.08E-05	-0.59		
RCMS4	1.82E-01	1.36		
WMS4	6.50E-03	0.26		
Log likelihood - full model			(base) -9449.81	(reduced) -9459.08
Log likelihood - constants only			-11231.79	-11231.79
Log likelihood - no coefficients			-12713.70	-12713.70

*Parameter is significant with 95% confidence. CC = vehicle purchase price; FC = fuel cost; SUB = government subsidy; RC = refueling convenience; W = warranty coverage, HASC = hydrogen fuel cell vehicle alternative specific constant; CCMS2 for example = interaction term between contribution to utility from capital cost and belonging to market share group 2 (in other words, whether belonging to market share group 2 has an effect on the value of vehicle purchase price in decision-making)..

Chow Test Model with Respondent Characteristics

The initial model specification included the following personal characteristics:

- Income group (Y), where income groups were entered as midpoints: 10 000, 17 500, 22 500, 27 500, 32 500, 37 500, 45 000, 55 000, 65 000, 72 000, 87 500, and 100 000.
- Age (AGE), where age groups were entered as midpoints: 24 and under = 20; 25-34 = 30; 35-44 = 40; 45-54 = 50; 55-64 = 60; over 65 = 70.
- Gender (M or F)
- Home region, ATL (Atlantic provinces), PRA (Prairie provinces), QC (Quebec), ON (Ontario) and BC (British Columbia).
- Respondents' willingness to pay a premium for ecologically-friendly technologies, yes (YEC) or no (NEC)

- Respondents' willingness to pay a premium for ecologically-friendly technologies that provide personal benefit, yes (YOW) or no (NOW).
- Whether the respondent was categorized as an innovator (INN), laggard (LAG) or early majority (EMA).

As was the case in the "Basic Model with Respondent Characteristics", collinearities among explanatory variables prevented me from estimating an MNL model with all the personal attributes at the same time. So, I estimated two models, one containing the home region and the other with income and age.

Chow Test Model with Respondent Characteristics (Nobs = 18,342) (Region)				
	Base Model		Reduced Model	
Attributes	ß parameter	t-ratio	ß parameter	t-ratio
CC	-1.56E-04	-19.56*	-1.46E-04	-29.89
FC	-2.34E-02	-2.72*	-1.75E-02	-4.44
SUB	3.04E-04	11.67*	2.91E-04	19.13
RC	9.22E+00	29.89*	9.23E+00	31.11
W	1.48E-01	8.06*	1.43E-01	15.82
CCMS2	-3.40E-05	-2.88*	-4.36E-05	-5.31
FCMS2	9.17E-03	0.82		
SUBMS2	-1.10E-05	-0.28		
RCMS2	-6.17E-01	-4.48*	-5.46E-01	-6.63
WMS2	-3.27E-02	-1.29		
CCMS3	-3.07E-05	-2.65*	-3.26E-05	-3.95
FCMS3	-6.22E-03	-0.53		
SUBMS3	9.54E-05	2.50*	1.20E-04	3.87
RCMS3	-1.16E-02	-0.08		
WMS3	9.54E-03	0.37		
CCMS4	2.42E-05	2.25**		
FCMS4	2.04E-02	1.71		
SUBMS4	-1.48E-05	-0.41		
RCMS4	1.68E-01	1.22		
WMS4	5.50E-03	0.21		
HASC	7.31E+00	26.78*	7.24E+00	26.91
HxEMA	-5.23E-01	-3.55*	-3.70E-01	-5.64
HxLAG	-9.99E-01	-6.46*	-8.51E-01	-10.05
HxINN	-2.07E-01	-1.28		
HxYOW	6.33E-02	0.78		
HxNOW	-3.36E-02	-0.33		
HxYEC	9.20E-01	13.58*	8.90E-01	15.65
HxNEC	-3.14E-01	-3.91*	-3.56E-01	-5.03
HxON	2.01E-02	0.19		
HxATL	-8.31E-02	-0.68		
HxBC	2.39E-01	2.11*	2.36E-01	4.11
HxPRA	7.98E-03	0.07		
HxQC	3.95E-01	3.71*	3.80E-01	8.41
HxF	1.05E-02	0.25		
Log likelihood - full model			-8962.91	-8976.32
Log likelihood - constants only			-11231.78	-11231.78
Log likelihood - no coefficients			-12713.70	-12713.70

*Parameter is significant with 95% confidence. **Parameter becomes insignificant with re-estimation. CC = vehicle purchase price; FC = fuel cost; SUB = government subsidy; RC = refueling convenience; W = warranty coverage, HASC = hydrogen fuel cell vehicle alternative specific constant; CCMS2 for example = interaction term between contribution to utility from capital cost and belonging to market share group 2 (in other words, whether belonging to market share group 2 has an effect on the value of vehicle purchase price in decision-making). HxZ = interaction term between HASC and personal attribute, representing the effect of Z personal attribute on respondents' utility for hydrogen fuel cell vehicles.

Chow Test Model with Respondent Characteristics (Nobs = 18,342; 1890 skipped) (Income and age)				
	Base Model		Reduced Model	
Attributes	ß parameter	t-ratio	ß parameter	t-ratio
CC	-1.71E-04	-18.71*	-1.73E-04	-31.27
FC	-3.38E-02	-3.44*	-2.48E-02	-5.31
SUB	3.08E-04	10.55*	3.17E-04	20.36
RC	9.53E+00	28.98*	9.51E+00	30.13
W	1.56E-01	7.87*	1.49E-01	15.51
CCMS2	-3.21E-05	-2.44*	-2.98E-05	-3.18
FCMS2	2.24E-02	1.83		
SUBMS2	1.72E-05	0.41		
RCMS2	-7.00E-01	-4.73*	-5.37E-01	-6.03
WMS2	-3.99E-02	-1.47		
CCMS3	-1.55E-05	-1.22		
FCMS3	5.29E-03	0.42		
SUBMS3	9.68E-05	2.31*	6.43E-05	3.02
RCMS3	-3.24E-02	-0.21		
WMS3	6.71E-03	0.24		
CCMS4	3.96E-05	3.30*	3.05E-05	4.90
FCMS4	3.46E-02	2.61*	3.30E-02	3.55
SUBMS4	-1.11E-05	-0.28		
RCMS4	1.60E-01	1.08		
WMS4	8.48E-03	0.31		
HASC	8.73E+00	14.23*	7.93E+00	26.28
HxEMA	-4.30E-01	-4.64*	-4.20E-01	-4.56
HxLAG	-8.93E-01	-8.26*	-8.90E-01	-8.28
HxYOW	8.68E-02	1.03		
HxNOW	2.47E-02	0.24		
HxYEC	8.80E-01	12.66*	9.00E-01	13.56
HxNEC	-3.60E-01	-4.36*	-3.52E-01	-4.52
HxAGE	-1.92E-03	-1.11		
HxY	-4.81E-06	-6.41*	-4.88E-06	-6.62
HxF	-7.80E-01	-1.49		
HxM	-7.44E-01	-1.42		
Log likelihood – full model			-7972.76	-7983.27
Log likelihood – constants only			-10117.12	-10117.12
Log likelihood – no coefficients			-11403.65	-11403.65

*Parameter is significant with 95% confidence. **Parameter becomes insignificant with re-estimation. CC = vehicle purchase price; FC = fuel cost; SUB = government subsidy; RC = refueling convenience; W = warranty coverage, HASC = hydrogen fuel cell vehicle alternative specific constant; CCMS2 for example = interaction term between contribution to utility from capital cost and belonging to market share group 2 (in other words, whether belonging to market share group 2 has an effect on the value of vehicle purchase price in decision-making). HxZ = interaction term between HASC and personal attribute, representing the effect of Z personal attribute on respondents' utility for hydrogen fuel cell vehicles.

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