COMBINING STATED AND REVEALED CHOICE RESEARCH TO INFORM ENERGY SYSTEM SIMULATION MODELS: THE CASE OF HYBRID ELECTRIC VEHICLES

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ABSTRACT

This study estimated dynamic behavioural parameters for an energy-economy model (called CIMS) using discrete choice modelling techniques, focusing on hybrid-electric vehicles (HEVs) . An online survey collected stated preference (SP) data from Canadian and Californian vehicle owners under different hypothetical market conditions. Revealed preference (RP) data was collected by eliciting the year, make and model of recent vehicle purchases. SP and RP data were combined in a 'joint' multinomial logit modelling technique, yielding choice models that were more realistic and useful than models estimated from SP or RP data alone. Dynamic behavioural parameters were estimated from the joint choice models and integrated into CIMS, significantly altering HEV adoption forecasts. Policy simulations with the improved model demonstrate the potential efficiencies of policies that induce technological change by reducing a technology's non-financial costs (e.g. vehicle emissions standard), as opposed to targeting capital costs (e.g. subsidies) or fuel costs (e.g. gasoline tax).

Keywords: stated preference; revealed preference; choice model; climate policy; hybrid model; technological change

Subject Terms: Decision making -- Mathematical models; Decision making -- Simulation methods; Consumers' preferences -- Simulation methods; Climatic changes – Government policy; Energy policy -- Canada

EXECUTIVE SUMMARY

This study estimated dynamic behavioural parameters for a hybrid energy-economy model (called CIMS) using empirically derived choice models based on stated preference (SP) and revealed preference (RP) data. In CIMS, preference dynamics are represented with a declining intangible cost function, where the non-monetary costs of a new technology decrease as it gains market share, referred to as the ‘neighbour effect’.

SP and RP data for hybrid-electric vehicles (HEVs) were collected with an online survey of Canadian and Californian vehicle owners. An SP experiment was conducted by randomly assigning respondents to one of three hypothetical market share treatments (0.17%, 10% or 50% HEV market share). After this treatment, respondents completed 18 binary vehicle choice sets that portrayed conventional gasoline vehicles and HEVs with varying levels of purchase price, fuel cost, subsidy and horsepower. RP data was collected by eliciting the year, make and model of a vehicle recently purchased by respondents. An RP choice model was then estimated by drawing vehicle attributes and non-chosen alternatives from a vehicle attribute database. RP dynamics were assessed by comparing models estimated from regions with differing levels of HEV market penetration (Canada at 0.17% market share and California at 3.0% market share).

Multinomial logit models were estimated from SP data, RP data and a combination of both sources, referred to as a ‘joint’ model. SP models yielded significant attribute

coefficients (at 99% confidence level), but unrealistically high HEV constants. The SP models thus predict HEV market shares that are much higher than reality. The RP models yielded problematic attribute coefficients due to multicollinearity, but realistic vehicle class and HEV constants. The 'joint' SP-RP models successfully combined the reliable attribute coefficients of the SP models with the reliable vehicle class constants of the RP model.

The Canada and California joint models were then used to calculate the HEV intangible cost function in CIMS, as well as parameters representing the discount rate and market heterogeneity. Simulations with the improved model forecast that in the absence of policy, HEV market share will slowly increase from 0.9% in 2005 to 6% in 2015, levelling at 27% in 2025 (using gasoline prices forecasted by Natural Resources Canada). This adoption curve follows an s-shape consistent with the diffusion of innovations theory, and is largely driven by an HEV intangible cost function that starts high ($40,000) and steeply decreases to more competitive levels as HEV market share surpasses 5%.

The capabilities of the improved model were demonstrated with a series of policy simulations, exploring the effects of a carbon tax, hybrid subsidy program, feebate program, and vehicle emissions standard (similar to that enacted in California). This informal comparison demonstrates the potential efficiencies of policies that induce technological change by reducing a technology's intangible costs (e.g. vehicle emissions standard), as opposed to targeting capital costs (e.g. subsidies) or fuel costs (e.g. gasoline tax).

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ABBREVIATIONS

ASC	Alternative specific constant
BAU	Business as usual
CC	Capital cost
CO_2	Carbon dioxide
EMRG	Energy and Materials Research Group
FC	Fuel cost
GHG	Greenhouse gas
HEV	Hybrid-electric vehicle
IPCC	Intergovernmental Panel on Climate Change
ITC	Induced technological change
IV	Inclusive value
LCC	Life cycle cost
LL	Log likelihood
MLE	Maximum likelihood estimate
MNL	Multinomial logit
NRC	Natural Resources Canada
OC	Operating cost
RP	Revealed preference
SP	Stated preference
VES	Vehicle emissions standard

CHAPTER 1: INTRODUCTION AND BACKGROUND

Technology is a major factor in many of Canada's environmental problems, including human-induced climate change. Although energy-using technologies are a major source of greenhouse gas (GHG) emissions, the development and adoption of low and zero emissions technologies could curb emissions growth without substantial changes in human activity. For example, the widespread adoption of hybrid-electric vehicles (HEVs) could reduce GHG emissions from passenger vehicles while meeting the same consumer demand requirements as conventional gasoline vehicles (kilometres travelled, personal comfort, etc.). This process of technological development and adoption is referred to as technological change. Policymakers are increasingly looking towards technological change as a powerful lever in meeting environmental objectives. This study explored how an energy-economy model could more realistically represent consumer behaviour when simulating policies that induce technological change. Specifically, I investigated how consumer preferences shift as a technology becomes more prevalent in the market, a tendency referred to as the 'neighbour effect'. Focusing on HEVs, I used an empirical methodology to derive behaviourally realistic choice models which I used to inform CIMS, an energy-economy model representing the Canadian economy. I then used this improved model to forecast the impacts of potential climate policies in the transportation sector.

This chapter provides a background of the various topics addressed in this study. First, I discuss the challenges facing environmental policymakers and outline how policies can induce technological change (Section 1.1). Then I briefly introduce the CIMS model and explain how it represents technological change and the neighbour effect with behavioural parameters (Section 1.2). Next, I discuss how the diffusion of innovations theory can guide expectations about the neighbour effect, providing a framework for empirical study (Section 1.3). Following this, I summarize the methods available to empirically derive behavioural parameters, comparing stated and revealed preference approaches for collecting data (Section 1.4). Finally, I provide a brief background of the hybrid-electric vehicle (Section 1.5), and conclude with a summary of my research objectives (Section 1.6).

1.1 Climate Change Policy and Technological Change

Climate change is thought to be one of the largest environmental threats facing humankind. The Intergovernmental Panel on Climate Change (IPCC) has complied extensive evidence supporting the hypothesis that temperature increases over the last century are largely driven by human-activity, particularly GHG emissions like CO_2 (Houghton et al., 2001). The Kyoto Protocol is the most well-known international climate change initiative, stipulating GHG abatement targets for most signatory countries. Canada committed to Kyoto in 2002, intending to reduce emissions to 6% below 1990 levels by 2010. Unfortunately, Canadian policy efforts have been unable to reduce emissions in the face of economic growth, and Canada is now over 20% above its Kyoto target (Environment Canada, 2004). A rough typology of policy alternatives can help explain Canada's current predicament in designing climate change policy.

Climate policy can reduce GHG emissions through two levers. First, a policy can focus on changing how consumers use existing technology, typically to consume less of a given service such as kilometres travelled in their vehicle. This consumption reduction focus is typically met with resistance by consumers, and is thus considered to be politically unpopular (Poortinga, Steg, Vlekb, & Wiersmac, 2003). The second lever is technological change, where a policy seeks to replace conventional technologies with low or zero emissions counterparts that provide the same basic service. This approach is increasingly being recognized among policymakers as the line of least resistance (Azar & Dowlatabadi, 1999). In addition to improved political acceptability, technological change policies are thought to effectively reduce the costs of emissions abatement (Goulder & Schneider, 1999; Goulder, 2004). Due to these benefits, this study focused on policies that induce technological change.

Policy approaches can be grouped into five categories: voluntary programs, command and control regulation, financial disincentives and incentives, and market-based regulation. Each approach has its strengths and weaknesses, which can be compared using the Canadian Government's framework for evaluating environmental tax proposals (Department of Finance Canada, 2005), summarized in Figure 1. Note that in addition to the overall environmental objective (effectiveness), a policy analyst is expected to clearly assess the fiscal impacts, economic efficiency, fairness, and simplicity of each alternative. These criteria can be used to compare the five main policy approaches.

Figure 1: Canada's Environmental Policy Analysis Criteria

Criteria for Evaluating Environmental Tax Proposals **Environmental effectiveness:** whether, and to what extent, the proposal will contribute to achieving the environmental goal. **Fiscal impact:** how the proposal will affect government expenditures or revenues. **Economic efficiency:** how the proposal will affect the allocation of resources in the economy and Canada's global competitiveness. **Fairness:** how the impacts of the proposal are distributed across sectors of the economy, regions or groups within the population. **Simplicity:** how governments will administer the proposal and how affected individuals or parties will comply—and at what cost.

Source: Department of Finance Canada (2005)

Voluntary programs are the least coercive of policy approaches, and have made up the bulk of Canada's climate strategy to date. Examples include the Voluntary Challenge and Registry program and information campaigns like the One-Tonne Challenge. This approach seeks to influence consumption patterns and promote the adoption of more efficient technologies without formal enforcement mechanisms. Although politically acceptable, programs such as these have proven to be ineffective in reaching abatement targets (Takahashi, Nakamura, van Kooten, & Vertinsky, 2001), and have had no perceptible effect on the trajectory of technological development in Canada.

In direct contrast to the voluntary approach, command and control regulation is the most forceful of policy categories. These policies stipulate specific technological standards or emissions levels that are enforced with penalties. Although this approach is effective in meeting specific emissions targets, it is criticized as an inefficient means of abatement. All firms are forced to adopt similar technologies or abate to the same level, even if they face vastly different costs. Also, this approach does not generate incentive for firms to innovate beyond the minimum compliance obligation.

A third class of policy makes use of financial disincentives. These are typically implemented as taxes to account for environmental costs not included in the market price of a product or process (externalities), such as the GHGs emitted by fossil fuel combustion.[1] Financial disincentives are generally more efficient than command and control regulation, providing a higher degree of freedom for firms and encouraging higher levels of technological innovation (Jaccard, Rivers & Horne, 2004). Unfortunately, deriving the optimal tax level for a given sector is a complex process which can send mixed signals to the market. In contrast, financial incentive programs offer subsides for environmentally benign technologies, and are more politically acceptable than the disincentive approach. However, incentive programs are vulnerable to free-riders, typically resulting in relatively low levels of effectiveness and efficiency (Jaccard et al., 2004).[2]

Lastly, market-based policy instruments score the highest across the framework criteria as summarized in Table 1. This approach can be just as effective as command and control regulation, but is far more flexible. Market based policies are designed to take advantage of naturally occurring market mechanisms to maximize the efficiency of

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[1] Such as a carbon tax, which would tax all GHG emissions at a set rate (e.g. \$100/ tonne of CO_2 equivalent).

[2] Free-riders are consumers that would have purchased the subsidized technology even in absence of the subsidy.

reaching an environmental target. Firms are typically allowed to trade emissions permits or credits on an open market, assuring that abatement occurs where the costs are lowest. The largest drawback of this approach is its complexity, as effective policy design requires a high degree of knowledge about the technological and behavioural constraints of the targeted sector.

Table 1: Evaluation of Basic Policy Options

Policy	Effective	Fiscal	Efficient	Fair	Simplicity
Voluntary Programs	Poor	Poor	Poor	Good	Medium
Command and Control	Good	Good	Poor	Poor	Good
Financial Disincentive	Medium	Good	Medium	Medium	Good
Financial Incentive	Medium	Poor	Poor	Medium	Medium
Market-Based Instruments	Good	Good	Good	Good	Medium

Source: Adapted from Jaccard, Rivers, & Horne (2004, p7)

The market based approach is an efficient means of inducing technological change. One branch of this approach is artificial niche market regulation, where a policymaker specifies a minimum market share for a low-emissions technology that increases over time (Jaccard et al., 2004). This approach takes advantage of two tendencies of the marketplace, learning-by-doing, and the neighbour effect. Firstly, the learning-by-doing effect is where manufacturers become more efficient at producing a new technology as they accumulate experience (Loschel, 2002). As production costs decrease, the low-emissions technology becomes increasingly competitive in the market. Secondly, the neighbour effect is demand driven, where the social costs of switching to a new technology decrease as the adoption rate increases. Technologies often become more desirable as they move into widespread use, due to changes in social concerns, increased credibility, and learning from others with more information (Yang & Allenby, 2003).

Through both of these forces, artificial niche market regulations stimulate the development and adoption of low-emission technologies to gain momentum until the policy is no longer required.

A vehicle emissions standard (VES) is a clear-cut example of an artificial niche market policy. A VES creates an artificial niche market for low and zero-emission vehicles, protecting new technologies as they develop to a point of competitiveness with conventional gasoline vehicles. California enacted a VES in 1990, stipulating that auto manufacturers had to sell a minimum market share of low and zero-emission vehicles by 2003, punishable by a per-vehicle fine. Despite administrative challenges and resistance from industry, the California VES has successfully shifted production efforts towards the development of hybrid-electric and hydrogen fuel cell vehicles (Kemp, 2002).

In general, market based policies hold potential for inducing technological change in Canada, but their relative complexity presents a challenge to policymakers and analysts. It is difficult to predict and assess the environmental and socioeconomic impacts of an induced technological shift across the economy, at both the transitional stage and in the long run. Analysts must consider the financial costs as well as the non-financial costs, or 'intangible costs' experienced by the economy when inducing technology change (Walls, 1996). Intangible costs include the many factors involved in switching technologies, such as consumer perceptions of quality loss or increased risk, and can be difficult to measure. Due to this complexity, policymakers may benefit significantly from policy simulation models that incorporate realistic intangible and financial costs when predicting the effectiveness and efficiency of a policy option.

1.2 Simulating Technological Change with an Energy-Economy Model

Energy-economy simulation models can assess and rank policy alternatives according to environmental effectiveness, abatement costs, or net changes in social welfare. There are a wide variety of energy-economy models in use today, which can vary dramatically in how they represent consumer behaviour, economic feedbacks, and technological change. Traditionally, models are divided between two classifications: bottom-up and top-down approaches (Loschel, 2002; Jaccard et al., 2003).

The bottom-up modelling approach is technologically explicit, detailing current and future energy technologies according to cost and performance characteristics. Bottom-up models estimate the costs of technological change, where the adoption of new technologies is driven by financial savings. However, this approach holds two main weaknesses. First, bottom-up models are not behaviourally realistic, as they ignore the intangible factors that inevitably influence technological choice, such as perceptions of risk and quality of service. Secondly, this approach does not account for macroeconomic feedbacks, such as rebound effects, where increased energy efficiency can decrease the cost of energy services and stimulate increased consumption. For these reasons, bottom-up models tend to underestimate the true cost of inducing technological change (Jaffe & Stavins, 1994).

In contrast, top-down models take a highly aggregated approach, representing economic sectors in term of inputs and outputs. Technological change is simulated with two indices: the elasticity of substitution (ESUB) and the autonomous energy efficiency index (AEEI). ESUBs represent the substitution between inputs that are driven by price. The AEEI is a general parameter that represents the non price-induced energy efficiency improvements in the economy. Both parameters are usually derived from long-run time series data, adding a degree of behavioural realism relative to the bottom-up approach. In addition, the inclusion of multiple sectors incorporates realistic macroeconomic feedbacks that are not present in bottom-up models. However, a major critique of top-down models is that historically derived behavioural parameters may not be appropriate for models making long-run forecasts (Grubb, Kohler, & Anderson, 2002). In addition, top-down models tend to overestimate abatement costs because the economy is assumed to be in a state of equilibrium, where any shift from this state is suboptimal (Jacobsen, 1998). Lastly, because top-down models are not technologically explicit, they are not effective for modelling policies that focus on particular technologies, such as a vehicle emissions standard.

In effort to consolidate the strengths of top-down and bottom-up modelling paradigms, a recent 'hybrid' modelling approach has emerged (Bohringer, 1998; Jaccard et al., 2003). A hybrid energy economy model seeks to attain a high degree of technological explicitness (like bottom-up models) as well as behavioural realism and macroeconomic feedback (like top-down models). One such hybrid model is CIMS, housed at the School of Resource and Environmental Management at Simon Fraser University. CIMS simulates the costs and environmental effects of abatement policies over a series of 5-year periods to aid in policy analysis decisions. CIMS can be used to estimate the long term costs of induced technological change, as well as forecasting a technology's market penetration, and effect on aggregate GHG emissions.

CIMS incorporates all three aspects of hybrid models. First, CIMS is technologically explicit, detailing over 1000 technologies. For instance, passenger vehicle technologies include conventional gasoline, hybrid-electric and alternative fuel vehicles. Second, CIMS contains a high level of macroeconomic feedback by estimating the extensive impacts of abatement policy on the economy, including shifts in supply and demand for certain service and products. Lastly, CIMS incorporates a degree of behavioural realism, simulating the preferences of consumers as elicited from empirical research.

This study focused on improving the behavioural realism of CIMS. In addition to financial costs, CIMS represents consumer preferences with three key behavioural parameters: the discount rate, intangible costs, and market heterogeneity. The market heterogeneity parameter represents how varied costs are across the economy.[3] While the discount rate and market heterogeneity parameters are the same for all technologies in a given node (such as passenger vehicles), the intangible cost parameter is unique for each technology. Intangible costs represents all the perceived costs (or benefits) of a technology that are not derived from its financial attributes (purchase price, maintenance costs, and fuel costs). Potential components of intangible costs include consumer perceptions of a technology's quality, reliability, availability, and in many cases, social desirability or popularity.

Recent improvements to the CIMS model allow financial and intangible parameters to change as a function of market conditions. These dynamics are represented with a function that allows the purchase price of new technologies to decline as more units are produced, simulating the learning-by-doing effect. A second function allows the intangible costs of a new technology to decrease as it gains market share, simulating the

[3] For instance, a high degree of market heterogeneity indicates that high cost technologies will still be adopted by some consumers for non-financial reasons.

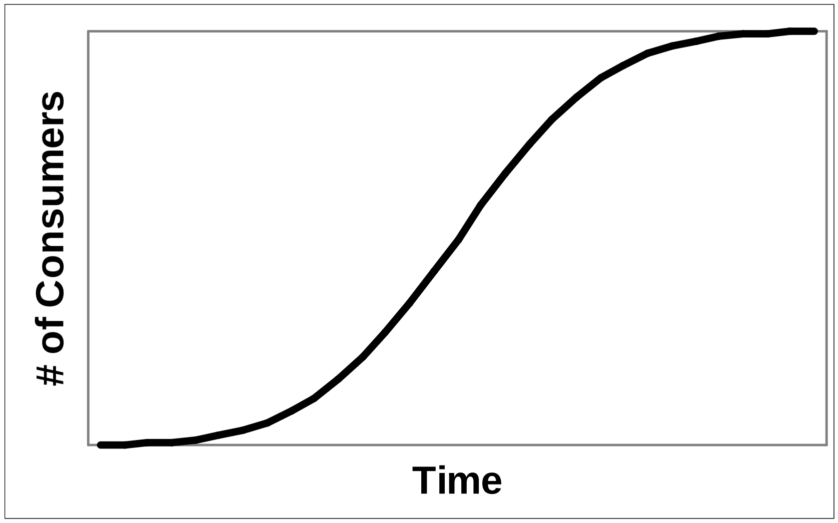
neighbour effect. However, a reliable method of quantifying the neighbour effect has not yet been established. Assigning static intangible costs assumes static consumer preferences, which contradicts research on preference dynamics, including the diffusion of innovations theory. I explore this research in the next section as a guide in formulating an empirical methodology to reliably represent the neighbour effect in CIMS.

1.3 Preferences Dynamics and Diffusion of Innovation Theory

While it may be acceptable to assume static consumer preferences in the short run, such an assumption is dubious when applied to long run forecasts. Indeed, preferences are known to continuously change and evolve, due to factors such as education, marketing and shifts in cultural norms (Norton, Costanza, & Bishop, 1998). These factors tend to change as certain technologies become more prevalent in the market. The diffusion of innovations theory helps to explain why such trends occur.

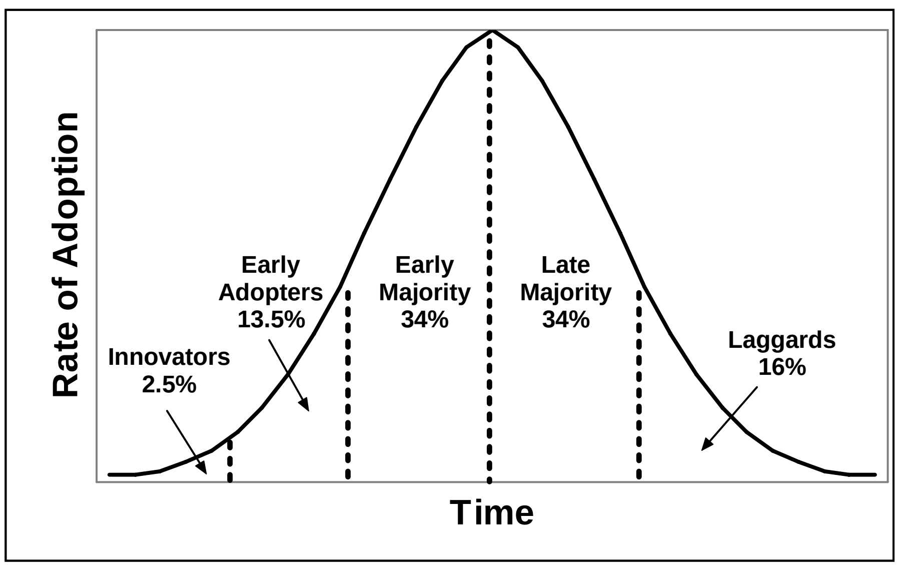
Diffusion is the process of communication and adoption of a new technology among the members of a social system. Everett Rogers (2003) first developed one of the most influential diffusion models in the 1960s. He discovered that in the typical process of diffusion, the total number of adopters (or sales) follows an s-shaped curve over time (Figure 2) and the adoption rate follows a bell-shaped distribution (Figure 3). He divided this adoption rate curve into five distinct consumer categories based on preferences for new technologies: innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%) and laggards (16%). Rogers' consumer classifications can be thought of as key stages in the diffusion process. If the diffusion of a new technology does not reach sufficient popularity in the innovator or early adopter stages, then it cannot achieve widespread adoption. This transition is often referred to as 'crossing the chasm'.

Figure 2: **Cumulative Adoption of Typical New Technology (S-Curve)**



Source: Adapted from Rogers (2003, p 11)

Figure 3: **Adopter Categories by Rate of Adoption**



Source: Adapted from Rogers (2003, p 281)

The diffusion process is largely driven by consumer preferences, derived from perceptions of the technology's attributes, risk, complexity, price, visibility in the market, and the degree of behavioural change required to adopt. These perceptions are thought to change because of communication channels or networks in the social system, where consumers influence the preferences of one another (Yang & Allenby, 2003). Rogers' diffusion model is a useful framework for the investigation of intangible cost dynamics. The intangible costs of a technology should be highest during the innovator stage, as consumer knowledge is at its lowest, and uncertainty at its highest. The greatest decrease in intangible costs should occur in the early adopter stage. Early adopters typically include many of the opinion leaders of a social system, and are thus expected to exert the greatest influence of the entire diffusion process (Smieszek, 2006). If the technology then diffuses to the early majority stage and beyond, intangible costs would continue to decrease at a slower rate, likely stabilizing at the late majority stage.

Although the neighbour effect is theoretically parallel to the diffusion of innovations theory, little empirical research has been conducted on intangible cost dynamics. Some recent research for the CIMS model has begun to investigate this effect, but the methodology is relatively new. The most challenging issue involves the dilemma of whether to use hypothetical (stated) or real (revealed) preference data to estimate the neighbour effect.

1.4 Stated and Revealed Consumer Preference Estimation

Behavioural parameters for most technologies in CIMS have been estimated through literature review, meta-analysis, judgment or expert opinion. Researchers prefer to base estimates on empirical data when possible, but sources are often unavailable, cost prohibitive, or incompatible with CIMS. Fortunately, discrete-choice modelling is compatible with the CIMS model and can be estimated from empirical data. Discrete choice models represent consumer preferences by quantifying the trade-offs made by consumers when choosing a technology. Choice analysis is a well-established field, and has been used to explore preferences for a variety of environmentally related technologies, including choices among appliances (Nanduri, Tiedemann, & Bilodeau, 2002), energy suppliers (Goett, Hudson, & Train, 2000), and of particular relevance, low-emissions vehicles (Ewing & Sarigollu, 2000). Choice models can be estimated from either stated preference (SP) or revealed preference (RP) data. Each approach has its own strengths and weaknesses, summarized in Table 2.

RP models are derived from real choices in the marketplace, and are thus a more realistic representation of the world. RP models fully account for the constraints facing consumers, such as income level and access to technologies. For these reasons, the RP approach is highly reliable and valid. However, RP data are limited to the technologies and conditions existing in the current (or past) market and are thus difficult to extrapolate to new market conditions, such as a scenario of dramatically different technological diffusion. In addition, RP models tend to suffer from modelling problems, where it is difficult to estimate the effects of individual factors because they varied little historically or changed in the same way (were collinear). For instance, vehicles with more engine power tend to be more expensive, and less fuel efficient.

In contrast, SP models are derived from hypothetical choice sets, where individuals indicate what they would choose under a range of hypothetical circumstances. These types of surveys overcome many of the 'real world' limitations of RP data, allowing researchers to customize the range of investigated technologies, attributes and other market conditions. This flexibility is particularly useful in forecasting the impacts of technological change. Unfortunately, this same flexibility is also the major drawback of SP data collection, as it allows respondents to make unrealistic decisions. This problem can stem from many human biases, such as the tendency for respondents to choose ‘socially desirable’ options more often then they would in real life to enhance their self-image (Urban et al., 1996).

Table 2: Comparison of Stated and Revealed Preference Approaches

	SP Data	RP Data
Strengths	- flexible attribute specification - new technologies - hypothetical scenarios	- real world - behaviourally dependable
Weaknesses	- unrealistic constraints - susceptible to respondent bias	- limited to current technologies - collinearity problems

Previous research has investigated the use of SP choice models to inform CIMS. Recent studies investigated neighbour effects for hybrid-electric (Mau, 2005) and hydrogen fuel-cell vehicles (Eyzaguirre, 2004). An RP methodology was infeasible at the time of data collection, as both vehicle technologies had achieved negligible or zero market penetration in the Canadian market where the studies were conducted. Although both studies produced informative results, the SP based parameter estimates were regarded with relatively low confidence, in part due to their hypothetical nature.

A growing body of research indicates that in some cases, SP and RP data can be combined to produce a joint model that may improve upon a model based on SP or RP data alone (Hensher, Rose & Greene, 2005; Train, 2003; Brownstone, Bunch and Train, 2000). This fusion can be done in a variety of ways. At a simple level, RP data can be collected simply to confirm the predictive validity of SP data (Whitehead, 2005). At a more advanced level, SP and RP data can be used together to estimate a ‘joint model’ (Revelt & Train, 1998). This method of joint analysis is explored in this study for estimating preference dynamics for the CIMS model. Hybrid-electric vehicles are an ideal technology to test this joint method.

1.5 Technological Change in Transportation: Hybrid Electric Vehicles

HEVs combine a conventional internal combustion engine with an electric motor. HEVs are typically 20-40% more fuel efficient than comparable gasoline vehicles, reducing GHG emissions by an equivalent proportion. HEV technology was a focus of this study for several reasons. First, the road transportation sector is a large source of GHGs, responsible for approximately 20% of Canada's total GHG emissions (Environment Canada, 2004). The widespread adoption of HEVs would improve the efficiency of the entire vehicle fleet and could substantially reduce national emissions.

In addition, the HEV is an appealing means of technological change because it has the attributes of an evolutionary technology, as opposed to a revolutionary technology. Evolutionary technologies can significantly reduce emissions while providing the same basic service as conventional technologies (such as independent personal travel), requiring little change in infrastructure or consumer preferences. In contrast, revolutionary technologies like hydrogen-fuel cell vehicles require a substantial shift in technology, energy form, refuelling infrastructure, attitudes and perceptions of risks (Adamson, 2003). The relatively non-disruptive diffusion process of the HEV could explain why this technology emerged from California's 1990 vehicle emission standard, which initially intended to boost zero-emission electric vehicles (Kemp, 2002).

The HEV was also an ideal technology for this study because it has had nearly 6 years to diffuse in the North American vehicle market since commercial introduction in

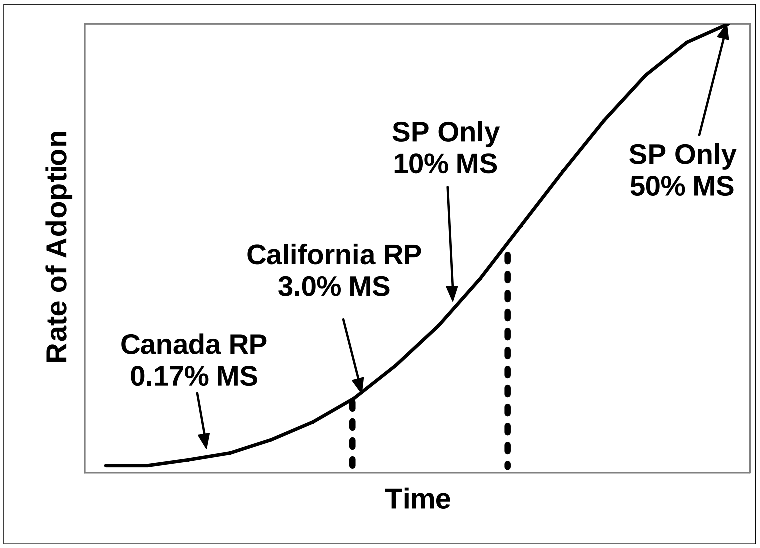
2000. Thus, it was possible to collect rich enough RP data from this period to estimate significant models. In particular, I was able to estimate RP dynamics by comparing two regions demonstrating different stages of diffusion: Canada and California. HEV market penetration has remained relatively low in Canada, making up only 0.17% of new vehicle purchases in 2005 (Table 3). In contrast, HEV sales have consistently grown in California to a 3.0% market share in 2005. Following Rogers' diffusion model, Canada is classified as an innovator based HEV market, while California has progressed to the early adopter stage, depicted in Figure 4. Thus, I expected an empirical study to reveal different intangible cost perceptions among Canadian and Californian vehicle consumers. Unfortunately, no regions have advanced beyond the early adopter stage, so I had to rely on hypothetical SP data to investigate more advanced diffusion scenarios (10% and 50% in Figure 4).

Table 3: HEV Market Penetration in Canada and California

	Canada		California	
	Share	**Stage**	**Share**	**Stage**
2003	0.03%	Innovator	0.7%	Innovator
2004	0.13%	Innovator	1.5%	Innovator
2005	0.17%	Innovator	3.0%	Early Adopter

Sources: Autonews (2006) and R.L. Polk & Co. (2006)

Figure 4: HEV Market Penetration Scenarios (SP and RP)



Like any new technology, the future of HEVs is uncertain. Assumptions about the trajectory of HEV development can be derived from current trends. Most of the 11 hybrid models available in 2006 have a higher purchase price, higher fuel efficiency, and lower horsepower rating than comparable conventional gasoline vehicles. However, it may be short sighted to assume the specific attributes of current HEVs represent the future of HEV technology. Purchase prices will likely decrease, and fuel efficiency increase, as manufacturers accumulate production experience. Similarly, some researchers predict that HEVs will develop to be more powerful than comparable gasoline vehicles, as already seen with the increased horsepower of the 2006 Honda Accord Hybrid. Another variation that is currently being developed is a 'plug-in' feature that allows HEV batteries to be charged overnight through the existing power grid. Despite these and other development possibilities, the economic models derived in this study assume that the physical attributes of future HEVs will be the same as present day.

The future demand for HEVs is uncertain. For instance, US forecasts of HEV diffusion range from a peak of 3% market share in 2011 (J.D. Power and Associates, 2005) to a steady increase up to 10-25% market share by 2020 (D. Greene, Duleep, & McManus, 2004). This disagreement among penetration forecasts largely stems from uncertainty about the evolution of consumer preferences. For example, one survey estimates that 68% of Canadians would seriously consider buying an HEV car as their next purchase (Canadian News Wire, 2005), yet respondents to the Canadian Auto Agency's *Autopinion* (2003) rated environmental friendliness as the least important car attribute of the 14 listed. Typically, however, this type of opinion survey is of limited value because respondents are not placed in realistic choice situations requiring tradeoffs among vehicle attributes, costs and environmental considerations. Without reliable knowledge of how consumers actually choose vehicles, it is difficult to forecast the evolution of HEV popularity with confidence. This study seeks to clarify many of these uncertainties in order to produce diffusion forecasts with a higher degree of realism.

1.6 Summary and Research Objectives

This chapter discussed how policymakers are increasingly looking towards induced technological change to meet environmental objectives in Canada. Artificial niche market regulations, such as California's VES, were introduced as a particularly efficient policy approach that exploits naturally occurring tendencies in the market. CIMS was introduced as a hybrid energy economy model that can help policymakers design effective policies that induce technological change to meet emissions abatement targets. I described how this study seeks to improve the behavioural realism of CIMS through the derivation of empirical parameters that account for the neighbour effect. The neighbour effect is represented by a declining intangible cost function derived from a combination of stated and revealed preference data. HEVs were chosen as the low-emissions technology of focus, as they are still relatively new, and have diffused enough in the market to allow the collection of meaningful RP data. In summary, the main objectives of this research are to:

1. Empirically derive behavioural parameters representing HEVs in CIMS using a combination of stated and revealed preference data.
2. Formulate a reliable procedure to estimate the declining intangible cost function in CIMS to account for the neighbour effect.
3. Conduct uncertainty analyses on all parameter estimates and changes to the CIMS model.
4. Use the improved CIMS model to simulate policies that could induce the adoption of HEVs in Canada.

The remainder of this study discusses the achievement of these objectives. Chapter 2 explains the methodology, including a synopsis of the models used, the construction of an online survey, and several methods of estimating discrete choice models from survey data. Chapter 3 summarizes the results of the survey and the estimated choice models, and explains uncertainties in model estimates. In Chapter 4, the most reliable choice models are integrated into CIMS, and used to simulate policy options in Canada, including a gasoline tax, subsidy scheme, feebate and VES. Chapter 5 summarizes and provides recommendations for future research.

CHAPTER 2: METHODS

This chapter discusses the methods used to meet the objectives of this study, and is divided into four main sections. Section 2.1 summarizes the basic workings of CIMS and the discrete choice models used to derive behavioural parameters. I discuss the three choice model estimation procedures used in this study: the multinomial logit (MNL), the nested logit (NL), and the estimation of a joint model from stated (SP) and revealed preference (RP) choice models. I then describe how choice model coefficient estimates were integrated into CIMS. Section 2.2 discusses the collection of SP and RP data through an online survey linked to a vehicle attribute database. Section 2.3 details the experimental design of the survey, including the sampling strategy, the specification of attributes in the choice models, the manipulation of hypothetical market scenarios, and the presentation of SP choice sets. Finally, Section 2.4 discusses the importance of presenting and communicating uncertainty in model estimates, rather than relying on single ‘best-fit’ values. Three methods of uncertainty analysis are discussed: Bayesian probability densities, Monte Carlo simulation, and sensitivity analysis.

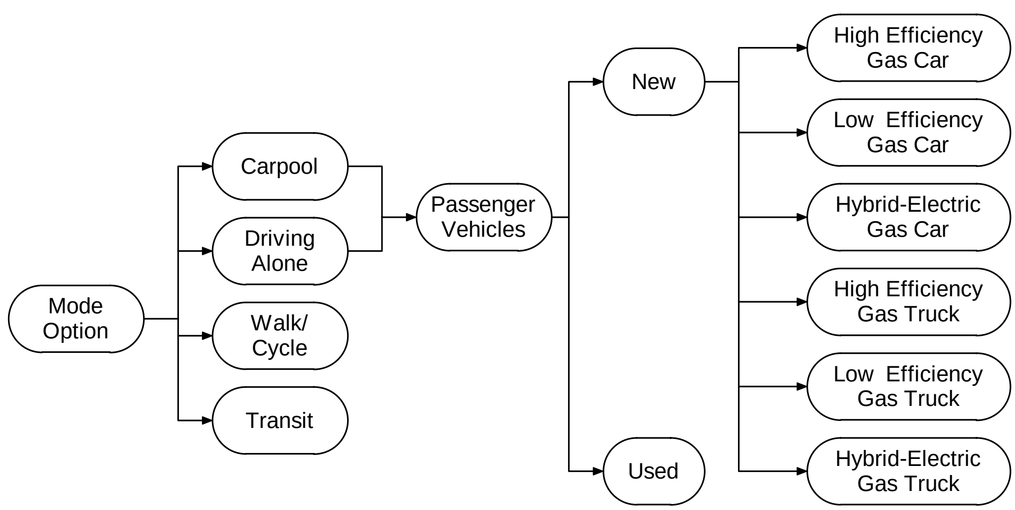
2.1 The Models

2.1.1 CIMS

As discussed in Chapter 1, CIMS is an energy economy model that simulates the costs and effects of a given abatement policy over a series of 5 year periods. As a technologically explicit model, CIMS details thousands of technologies throughout the

Canadian economy. Figure 5 outlines the personal transportation sector node used in this study. Total demand for this sector is represented in person kilometres travelled, which can be met by four modes: transit, walk/cycle, drive alone, or carpool. In the full CIMS model, both driving modes are divided into car and truck technologies that run on gasoline, propane, natural gas, diesel, methanol, ethanol, electricity, and hydrogen. However, CIMS is limited to only three gasoline-fuelled technologies for this study: low-efficiency, high-efficiency, and hybrid-electric vehicles. This simplification is necessary because this study only estimates preference dynamics for HEVs. It would not be appropriate to run simulations that 'compete' dynamic HEV specification with other new vehicle technologies that are held static.

Figure 5: CIMS Technology Node: Personal Transportation



To forecast the market trajectory of each technology in a given node, CIMS employs a market share function for new vehicle acquisition that considers both the financial costs and monetized quality attributes (intangible costs) of each technology. This function is represented as follows:

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

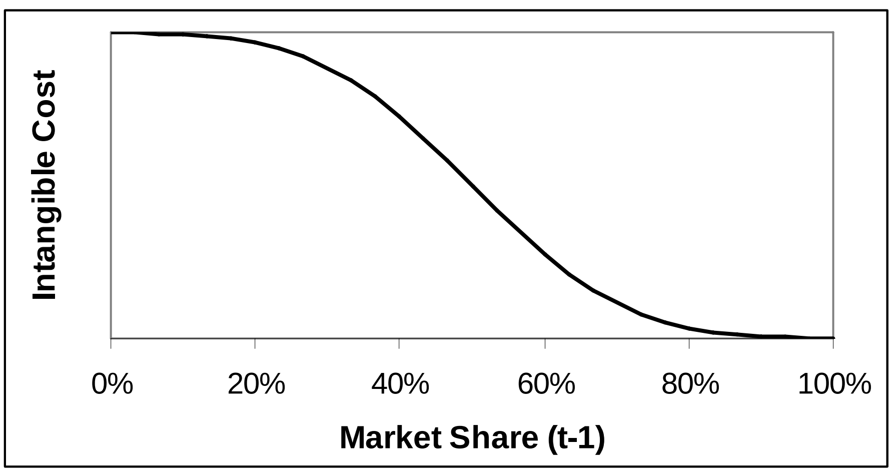
Where MS_j is the market share of technology j relative to technology set k. CC_j, MC_j and EC_j are the capital, maintenance and energy costs of j. Consumer behaviour is incorporated through the three behavioural parameters: i_j, the perceived intangible costs of j, r, the perceived discount rate of the decision maker and v, a measure of market heterogeneity (representing how varied costs are in the economy). Taken together, the sum of annualized capital cost, maintenance cost, energy cost and intangible cost represents the total cost of a technology, referred to as the lifecycle cost (LCC). The market heterogeneity parameter represents how varied the LCCs are across the economy, as experienced by different consumers and firms. A high v indicates that the technology with the lowest LCC captures most of the new market share. A low v indicates that the market shares of new technologies are distributed relatively evenly, even if their LCCs differ significantly.

The market share function has the capability to be dynamic, accounting for the learning-by-doing effect and the neighbour effect. The first is represented by the declining capital cost function, which allows CC_j to decline as production accumulates. This function is currently specified for HEVs, and was included in all simulation runs for this study. The neighbour effect is represented by the declining intangible cost function:

$$i(t) = \frac{i(0)}{1 + Ae^{k*MS_{t-1}}} \qquad \text{Equation 2}$$

Where *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 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. The default parameters of this function (*A* = 0.0065, *k* = 10) yield the s-curve presented in Figure 6. This study investigated this intangible cost curve using empirically derived discrete choice models, which have been established by previous researchers as a convenient method to estimate not only *i*, but also the *r* and *v* parameters.

Figure 6: Default Declining Intangible Cost Function



2.1.2 Multinomial Logit (MNL)

Discrete choice models analyze the behavioural process of an individual's choice among mutually exclusive options (Train, 2003), quantifying the trade-offs among product attributes. Previous research for CIMS used the multinomial logit (MNL), or ‘standard’ logit, model to empirically estimate behavioural parameters (Eyzaguirre, 2004; Mau, 2005; Rivers & Jaccard, 2005; Horne, Jaccard & Tiedemann, 2005). Similar to CIMS, the MNL is behaviourally realistic, technologically explicit, and can be designed to predict technology market share in different market scenarios.

The MNL is based on random utility theory, assuming that a portion of the utility derived by an individual is unobservable. Therefore, an individual’s utility is broken into two components, as represented by the following function:

$$U_j = V_j + \varepsilon_j \qquad \text{Equation 3}$$

Where U_j, the utility of choice j, is the sum of V_j, observable or ‘representative’ utility, and ε_j, unobservable utility. ε_j is treated as a random parameter with a mean of zero, following a Weibull distribution. The Weibull is a closed-form version of the normal distribution, which means that the distribution tails do not extend to infinity. This closed-form distribution simplifies the model, where estimates can be computed without the use of simulation. Observable utility, V_j, is represented as:

$$V_j = \beta^* X_j + ASC_j \qquad \text{Equation 4}$$

Where Xj is a vector of the attributes of choice j, β is a vector of coefficients weighting each of those attributes, and ASC_j is the alternative-specific constant, which represents the observable utility of each choice not captured by attributes specified in the model.

Similar to the market share function in CIMS, MNL models can estimate the probability of option *j* being chosen from choice set *k*, using equation 5. This probability can be equated with market share if the representative utility function is estimated from a large enough sample size, depicted as follows:

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

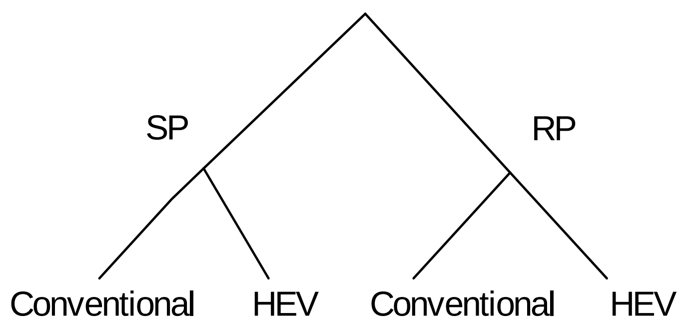
Where MS_j is the estimated market share of choice j, which compares the observable utility of choice j to the observable utilities across the choice set k.

The MNL is the most simple and widely used logit model, but this simplicity comes with a number of restrictions that are not appropriate for some applications (Train, 2003). For instance, the MNL does not allow for random variation in consumer 'taste' parameters (*β's*), unrealistically assuming that each estimated coefficient is the same for every individual. Although this assumption can misrepresent or oversimplify consumer preferences, it is consistent with the aggregated nature of the CIMS model and is not considered a significant limitation in this study.

2.1.3 Nested logit (NL)

The nested logit (NL) model is briefly introduced here as a tool to assist in the joint estimation of stated and revealed preference data (discussed in the next section). The NL is slightly more advanced than the MNL, relaxing assumptions in the variance components of the MNL model, but still uses the closed-formed Weibull distribution to simplify the estimation process (Hensher, Rose, & Greene, 2005). Conventionally, the NL represents consumer choice as a tree with several levels of decision, such as vehicle versus transit, and then type of vehicle. An MNL model is estimated separately for each branch, allowing a different error variance for each decision, which is more behaviourally realistic. However, this study does not employ the NL for its conventional use, but rather as a means of estimating scale differences between SP and RP based choice models. SP and RP models can be estimated simultaneously on different branches of the NL (Figure 7). In addition to coefficient estimates, the NL also estimates a unique inclusive value (IV) parameter for each branch (RP and SP). The IV represents the scale of each branch, and can be used to adjust the coefficients in separately estimated SP and RP models when forming a composite utility function.

Figure 7: Nested Logit – Tree Specification



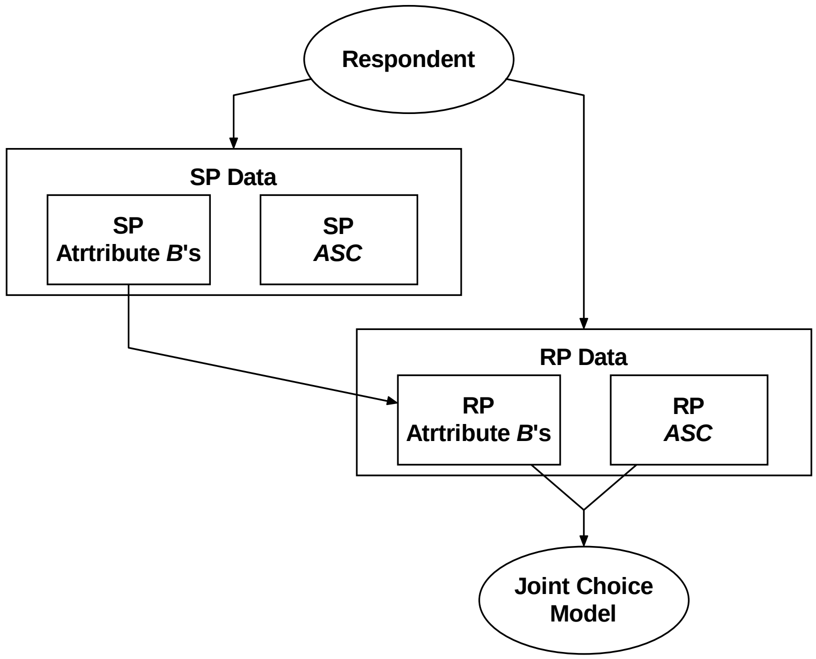
2.1.4 Joint Models: Combining Data Sources

Discrete choice models can be estimated from SP or RP data. As discussed in Section 1.4, there are many potential benefits to using both types of data, particularly for the research objectives of this study. Brownstone et al. (2000) combined SP and RP data to model vehicle preferences in California. The authors concluded that the RP data was helpful for realistically estimating body-type choices and scaling information, while the SP data gathered information about attributes not available in the market place. The resulting joint MNL model was more robust than either the SP or the RP models alone.

However, combining data sources is a complex process and requires a high degree of judgment on the part of the researcher. There are many different approaches to this type of estimation. Two main techniques are identified by Louviere, Hensher and Swait (2000): pooled and sequential estimation.

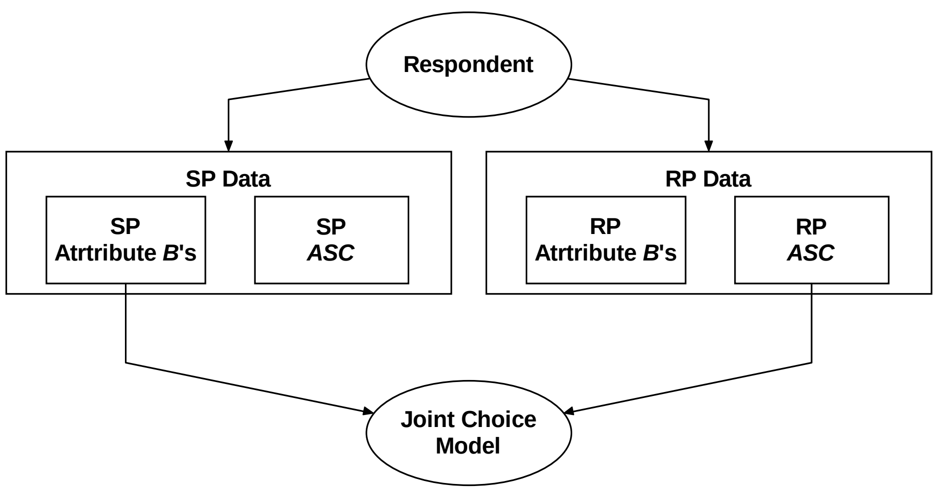
These approaches differ in how model coefficients are combined from the SP and RP data sources. Consider the two types of coefficients that make up the utility function in Equation 4. The attribute coefficients, or β's, represents the trade-offs among technology attributes. The constant term, or *ASC*, represents any alternative-specific utility not captured in the specified β's, and is responsible for calibrating RP models to fit observed market shares. The data pooling approach to joint estimation combines SP and RP data to estimate the β's from both sources, while the *ASC* is estimated from the RP data only (Figure 8). In contrast, the sequential approach estimates separate SP and RP models, then discards the SP *ASC* and the RP β's. The SP β's and RP *ASC* are placed in a composite utility function, where the RP *ASC* is recalibrated to fit the real-life market shares represented in the RP data (Figure 9).

Figure 8: SP-RP Joint Estimation – 'Pooling' Technique



Source: Adapted from Louviere et al. (2000)

Figure 9: SP-RP Joint Estimation – 'Sequential' Technique



Source: Adapted from Louviere et al. (2000)

Both methods of joint estimation have been successfully applied in various studies. However, it has been noted that the sequential technique more aptly exploits the strengths of both data sources, and is particularly useful when the RP data set contains a high degree of multicollinearity (Swait, Louviere, & Williams, 1994). This last point is relevant for vehicle choice models, where attributes are typically correlated because characteristics like price, fuel efficiency and power are closely related. Such collinearity leads to problematic RP β estimates. For this reason, the SP β's were expected to be far more reliable than the RP estimates, and thus the sequential approach to joint estimation was deemed more appropriate for this study.

In either approach to joint modelling, the researcher must account for the different 'scale' in observable utility (β and ASC coefficients) relative to unobservable utility (ε_j) when combining coefficients from different models. This stems from the fact that SP models hold constant all non-specified attributes, while RP models cannot, resulting in a larger ε_j variance for RP models. Train (2003), describes how to introduce a scale parameter, λ, to the utility functions of both models, where the RP scale factor, λ^r, would be normalized to zero, represented as:

$$U_{nj} = \beta^r * x_{nj} + ASC_j^r + \varepsilon_{nj} \qquad \text{Equation 6}$$

Where U_{nj} is the estimated utility of choice j for person n, and ASC^r and β^r are coefficients unique to the RP model. If β^s is to be extracted from an SP model and put into an RP model, it would first have to be adjusted by a scale factor, λ^s. The resulting composite utility function would be:

$$U_{nj} = (\beta^s / \lambda^s) * x_{nj} + ASC_j^r + \varepsilon_{nj} \qquad \text{Equation 7}$$

With this specification, λ^s reflects the variance of unobserved factors in SP situations relative to RP situations.

The scale parameter λ^s can be estimated using the nested logit model described in the previous section. As mentioned, the NL model estimates an IV parameter that represents the scale between two branches. By estimating the SP and RP models on two separate branches of the same model, λ^s is represented by the IV. Because there is no behavioural meaning to this nesting specification, this technique has been referred to as an "artificial tree structure" (Louviere et al., 2000, p 242). Hensher et al. (2005) recommend this technique in the sequential estimation approach. This sequential joint modelling technique helped to assure that coefficient estimates were meaningful and reliable before translating them into behavioural parameters for CIMS.

2.1.5 Translating Choice Coefficients into CIMS Parameters

Methods have been established to use choice model coefficients to inform the behavioural parameters used in CIMS. Specifically, these are the 'i', 'r' and 'v' parameters of Equation 1. First, the discount rate, '*r*' can be calculated using the following formula derived by Train (1985):

$$r = \frac{\beta_{CC}}{\beta_{OC}} \times (1 - (1 + r)^{-n}) \qquad \text{Equation 8}$$

Where 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.

Next, the intangible costs of HEVs can be calculated by comparing each non-monetary β coefficient (including the *ASC*) to the capital cost coefficient and summing all ratios. The non-monetary coefficients in this study are vehicle power and the *ASC*. This equation is depicted as follows:

$$i_j = \sum^{N}\left(\frac{\beta_n}{\beta cc} \times X_n\right) \qquad \text{Equation 9}$$

Where i_j is the perceived intangible costs of 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. The declining intangible cost function was introduced in Section 2.1.1 (Equation 2), and can be determined by estimating i parameter for several different HEV market share scenarios. The A and k parameters of this function can then be fit to the observed i's by using the Solver algorithm in the Excel spreadsheet software package.

The third behavioural parameter, v, cannot be estimated directly from the choice model parameters. Instead, v is estimated using Solver to find a value that comes closest to equating the CIMS market share function (Equation 1) with the market share forecasts of the choice models (Equation 5), represented in the following equation:

$$\frac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}} = \frac{(LCC_j)^{-v}}{\sum_{k=1}^{K}(LCC_k)^{-v}} \qquad \text{Equation 10}$$

Where *LCC* is the lifecycle cost of the technology, which is the sum of the annualized capital cost, maintenance cost, fuel cost and intangible costs (as represented in full in Equation 1).

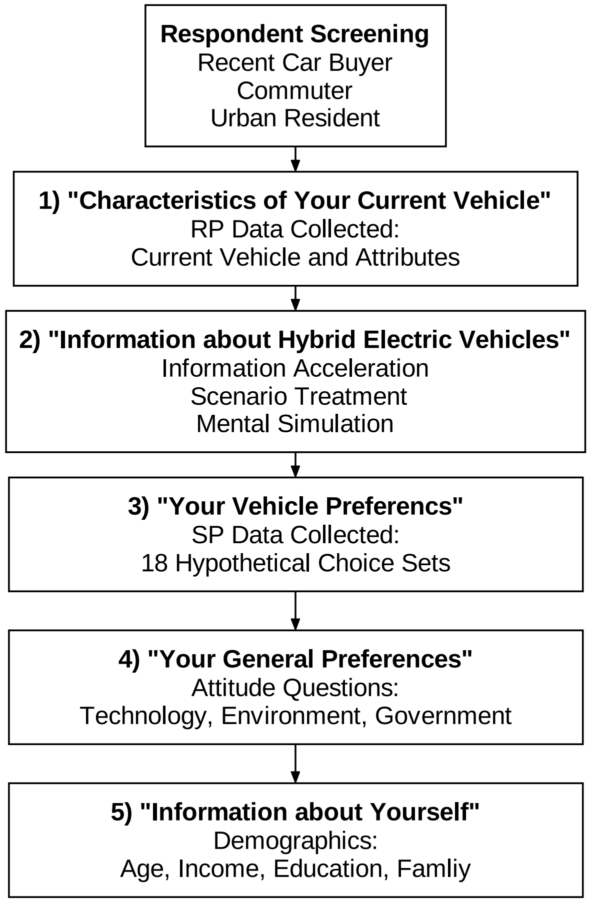
2.2 Data Collection

In order to investigate the neighbour effect using the models described above, this study gathered SP and RP data to estimate the intangible costs (*i*) of HEVs at different points in the diffusion process. Two *i* scenarios were estimated with RP data: one for Canada and one for California. Three *i* scenarios were estimated with SP data, using an 'information acceleration' experiment described in section 2.3. All SP and RP choice data used in this study were collected with an online survey, which was linked to a vehicle attribute database.

2.2.1 Online Survey

The internet is a very useful method of implementing surveys as it allows extensive use of visual aids, automates the customization of choice sets and collection of data, and expedites data analysis. Web-based surveys are also viewed as more confidential than paper-based or interviewer-administered surveys, lowering the likelihood of social desirability bias (Brace, 2004). A basic flow chart of the survey used in this study is depicted in Figure 10. While it is possible to collect RP data from means other than a survey, such as market data, I chose to collect both data types from the same respondents to maintain consistency. This consistency facilitated the estimation of joint SP and RP models. The full survey is presented in Appendix A.

Figure 10: Survey Design Flow Chart



The first portion of the survey screened respondents to assure they fit the study's criteria. To be eligible, respondents must have purchased a new passenger vehicle of model year 2002-2006, as this period coincides with the RP vehicle attribute database (described next) where HEVs were reasonably available in the market. Other criteria include being 19 years of age or older, commuting regularly, and residing in an urban centre. Following this, the first section of the survey elicited RP data, asking respondents to provide details about their primary vehicle. The next section provided basic information about HEVs. Respondents were then instructed to complete a series of 18 binary choices, each presenting an HEV and conventional vehicle with varying attributes.

The last two sections collected general attitudinal and demographic data from respondents. Although this survey was detailed enough to collect all necessary SP data, a vehicle database had to be linked to the survey to facilitate the collection of RP data.

2.2.2 Vehicle Database

To assure reliable RP data, I constructed a comprehensive vehicle database from a detailed 2003 fuel efficiency database provided by Natural Resources Canada (NRC). I adapted this database for 2002 and 2004-2006 by consulting fuel consumption guides (e.g. NRC, 2006), and vehicle information websites (e.g. Canadian Driver, 2006). The complete database specifies almost 1500 vehicle models (300 per year), detailing each model's retail price, fuel efficiency and horsepower. Vehicle class is also specified according an 11-class system used by NRC, based on a study by Greene, Patterson, Singh and Li (2005): subcompact/compact/midsized/large car, small/midsized/large SUV, mini/large van, and small/large pickup truck. This database facilitated the collection of the three components of RP data: 1) the respondents' actual purchase choice, 2) the attributes of that choice, and 3) the respondents' non-chosen alternatives and their attributes.

First, respondents' revealed choices were collected by eliciting the year, make and model of their 'primary' vehicle, the vehicle they drive most often (purchased new in 2002 or later). To stimulate the memory of respondents and maintain consistency among responses, drop down menus portrayed all models listed in the vehicle database. Manual entry was permitted for respondents that could not find their vehicle model listed.

Secondly, this standardized entry process allowed me to automatically draw the attributes of each vehicle from the vehicle database. This was helpful because attributes like horsepower and fuel efficiency ratings are typically not well known by vehicle owners (Kurani & Turrentine, 2004), so I was not confident in their estimates of these values. However, some attributes were more appropriate to record directly from respondents, such as purchase price and weekly fuel cost, which vary among individuals.

The final stage in collecting RP choice data was to record respondents' non-chosen alternatives (NCAs). At least one NCA must be specified for each respondent in order to model attribute tradeoffs among purchase options. One option was to ask respondents for their 'second choice' had their primary vehicle been unavailable. However, this method is unadvisable because a second choice is likely to have very similar attributes to the primary vehicle, and wouldn't produce sufficient variation to estimate a realistic model. Also, a consumer actually rejects all other available vehicle models when making a purchase decision, not just their second choice. Another option was to model all 300 non-chosen vehicles for a given model year from the database. Unfortunately, such an approach would be far too computationally straining. Brownstone et al. (2000) faced this same dilemma when designing an RP vehicle choice study. Their effective solution was to randomly select a subset of available vehicles for each respondent, which was compiled as a representation of each respondent's choice set.

Using this approach, I represent each choice set with 12 alternatives: one actual choice and 11 randomly drawn NCAs from different vehicle classes. The vehicle class alternatives consisted of HEVs, and 11 class categories for conventional gasoline vehicles following NRC's classification scheme. For example, if a respondent's primary vehicle was a 2003 Honda Civic, NCA vehicles would be randomly drawn for each class other than ‘compact car’. An example is presented in Table 4 below. This method assures that each choice set contains a significant degree of attribute variation, and realistically approximates the actual breadth of vehicle choices available to each consumer at the time of purchase.

Table 4: Example RP Choice Set

Class	Year	Make	Model	Chosen?
1 – Subcompact Car	2003	VW	Beetle	No
2 – Compact Car	**2003**	**Honda**	**Civic**	**Yes**
3 – Midsized Car	2003	Toyota	Camry	No
4 – Large Car	2003	Lincoln	Town Car	No
5 – Small SUV	2003	Honda	CR-V	No
6 – Midsized SUV	2003	Toyota	Highlander	No
7 – Large SUV	2003	Ford	Excursion	No
8 – Minivan	2003	Dodge	Caravan	No
9 – Large Van	2003	Ford	E150	No
10 – Small Pickup	2003	Dodge	Dakota	No
11 – Large Pickup	2003	Ford	F150	No
12 – Hybrid Electric	2003	Toyota	Prius	No

2.3 Experimental Design

This section describes the details of the experimental design of this study in four parts: 1) sampling strategy, 2) specification of attributes, 3) “information acceleration” treatment, and 4) choice set presentation.

2.3.1 Sampling Strategy

Sampling is said to be one of the least understood areas of choice analysis (Hensher et al., 2005), largely due to the complex nature of choice modelling. The two main considerations of a sampling strategy are the technique and the determination of sample size. First, there are two general sampling techniques: simple random sampling (SRS) and choice-based sampling (CBS). SRS consists of a straightforward random sample from the target population, and is appropriate for most SP choice experiments. However, RP choice models can be more complicated, as the SRS technique may not recruit a significant proportion of respondents owning a product with low market share, such as HEVs. Because HEVs make up only 0.17% of the Canadian vehicle market, it would be lucky to recruit even one HEV owner in a random sample of 500. A useful RP choice model could not be estimated with such a sample. The CBS technique overcomes this problem, as low-penetration technologies are purposely over sampled to assure that a valid model can be derived. When CBS data is entered into choice-modelling software, this overrepresentation is corrected by weighting the data to reflect the true market share.

After choosing a sampling technique, the targeted sample size must be determined. There is no widely accepted method for calculating sample size in choice models (Hensher et al., 2005). I chose to treat the technological market share as a simple population proportion, for which there are accepted sample size calculations. This formula is based on the desired minimum confidence level (Newbold, 1995), as follows:

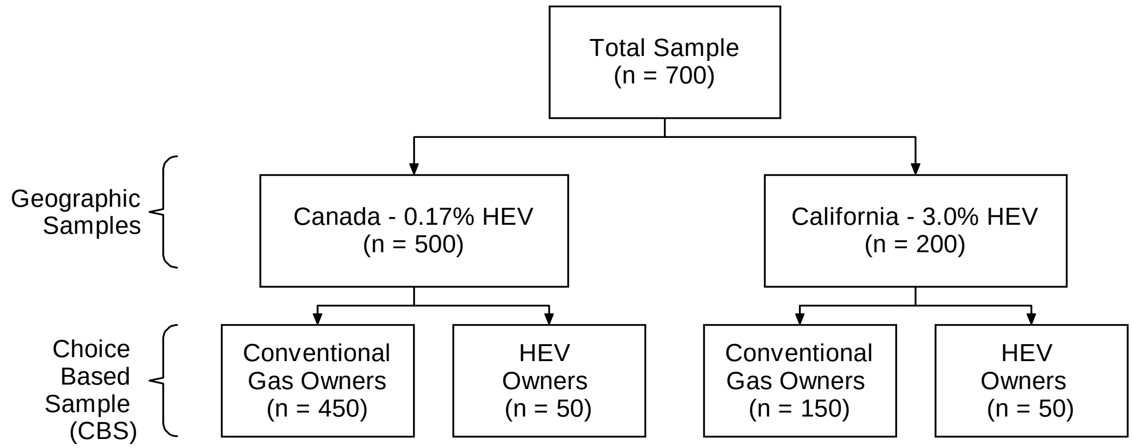
$$n = \frac{0.25 * z_{\alpha/2}^2}{L^2} \qquad \text{Equation 11}$$

Where n is the required sample size, z is the value for confidence level α, and L is half of the acceptable interval around the sample proportion. As an illustration, a sample of 384 respondents would be required for a interval within 5% of the estimated proportion (market share prediction) at 95% confidence.

On a more realistic note, Hensher et al. (2005) admit that sample size is more often determined by funding constraints than by statistical optimization. As a rule-of-thumb, they state that a minimum of 50 respondents be recruited for each choice modelled. I followed this simple rule for HEV owners in the RP choice models, as this segment proved very difficult and expensive to recruit. The conventional gasoline vehicle segment is much more prominent, giving me the budgetary flexibility to aim for 450 Canadian respondents, which would keep market share confidence intervals within 5.0%. Because the California sample was not as important to this study, the three segment group targets were also limited to the minimum of 50 respondents (150 total).

The collection of SP data is more flexible due to its hypothetical nature. CBS was not required in theory, but was necessary because the SP and RP data were collected from the same survey. Respondents were randomly divided into three hypothetical market share treatment groups, and each respondent completed 18 SP choices. The 450 respondents targeted in the Canadian conventional gasoline vehicle sample would give 2,700 choice observations per treatment group. Using Equation 11, this would yield a +/- 2% confidence interval. The California SP sample target was limited to 900 choice observations per treatment, corresponding with a slightly wider confidence interval of just over +/- 3%. The entire sampling strategy is depicted in Figure 12.

Figure 11: Sampling Strategy



This sampling strategy was implemented by two market research companies, one for Canada, and one for the US. Respondents were drawn from online panels constructed by each firm. Admittedly, this recruitment strategy is not truly random, and is subject to bias, such as a potential overrepresentation of technology-savvy consumers. However, these effects were expected to be minimal. In addition, the company that recruited the main Canadian segment (which was of primary importance in this study) handpicked the sample to assure adequate representation of the Canadian population, including population and income distributions.

2.3.2 Setting Vehicle Attributes

In SP experiments, hypothetical choice sets can present any set of attributes desired by the researcher. This selection of attributes and attribute levels can have dramatic effect on model outcomes, and is thus a very important stage of the experimental design process. In reality, consumers may consider any number of attributes when choosing among vehicles, ranging from price and reliability to color and style. However, if a choice model specifies too many attributes, the model unnecessarily loses degrees of freedom and explanatory power. On the other hand, if too few (or unimportant) attributes are included, then the majority of consumer utility is captured with the *ASC*, and important attribute trade-offs are ignored. Choice modellers try to balance these extremes by specifying a parsimonious model, one that is both simple and meaningful. I attempted to reach this middle ground by focusing on only four key attributes: capital cost, fuel cost, subsidy, and power. There are three main reasons for this selection.

First, these attributes are important for deriving the behavioural parameters for CIMS. Equation 8 shows that the discount rate 'r' is calculated from capital and fuel costs coefficients. Equation 9 shows that the intangible cost parameter 'i' is also calculated from a capital cost coefficient, as well as non-monetary intangible coefficients. Vehicle power was specified in this model as the main 'intangible' coefficient, as research indicates that it is one the most important attributes considered by vehicle consumers (Canadian Auto Agency, 2003; Horne, Jaccard, & Tiedemann, 2005). Any remaining intangible attributes were captured by the *ASC*. Government subsidy was specified separately to capital cost because research indicates consumers may weigh the dollar value of a subsidy disproportional to equivalent savings in capital cost (Mau, 2005).

A second reason for this selection of attributes is that they represent most of the key differences between HEVs and conventional gasoline vehicles. Generally speaking, HEVs are currently more expensive (by 15-30%), more fuel efficient (by 20-40%), less powerful (by 15-25%) and more eligible for subsidies ($500-$3000) than comparable conventional vehicles. These differences are likely to continue into the foreseeable future, although the magnitude may decrease at higher diffusion levels. As noted in Section 1.5, the power of the average HEV has the potential to surpass that of conventional gasoline vehicles, but this study assumes that HEVs will remain less powerful.

A final reason for this selection of SP attributes is that RP data was readily available for most of them (except subsidy). The vehicle database described in section 2.2.2 includes values for capital cost, fuel efficiency, and horsepower. This consistency eased the process of estimating joint models from SP and RP data.

Table 5: Attributes Included in Previous Vehicle Choice Experiments

	Attributes						
Studies	**Capital Cost**	**Fuel Costs**	**Subsidy**	**Power**	**Fuel Range**	**Warr anty**	**Class/ Model**
Bunch et al. (1993)	X	X		X	X		X
Brownstone et al. (2000)	X	X		X	X		X
Ewing and Sarigöllü (2000)	X	X		X	X		
Eyzaguirre (2004)	X	X	X			X	X
Greene et al. (2005)	X	X	X				
Horne et al. (2005)	X	X		X			
Mau (2005)	X	X	X		X	X	X
This Study	X	X	X	X			X*

* included in SP market share scenario treatment and RP model, but not SP choice sets

Table 5 portrays some of the attributes that are typically included in similar vehicle choice studies. I have not include fuel range (distance travelled per gas tank) or warranty period in this study. I assume that fuel range would be proportional to fuel efficiency and does not need to be addressed separately. I also assume that automakers are likely to offer similar warranty packages for HEVs as conventional vehicles. There are many other non-monetary attributes that I have excluded in Table 5, such as reliability, safety, commuting time and comfort. All non-specified attributes are considered to be ‘lurking’ variables, which can influence consumer choices if left unaddressed. Because the exclusion of these variables assumes they are constant across vehicle choices, I have taken steps to communicate these assumptions in the “information acceleration” portion of the study, described in the next section.

After specifying the attributes of an SP choice model, a researcher must determine what attribute levels to present in the hypothetical choice sets. Once again, this exercise requires a sense of balance, as these levels should vary enough to capture the various trade-off points that exist among consumers, while avoiding unrealistically high or low values. One method to help achieve this balance is described by Hensher et al. (2005), where the RP attribute levels entered by respondents are used as a base value for the SP attributes. I followed this method, specifying each attribute level as a percentage value that ‘pivoted’ around the RP base, instead of setting absolute values. Thus, the attribute levels remained in a range familiar to the respondent.

Table 6 depicts the SP attribute levels used in this study, with three levels per attribute. Capital costs ranged from 100-125% of the respondents’ purchase price for the gasoline vehicle, and up to 150% for HEVs. HEV subsidies could be either 0%, 5% or 10% of purchase price, which is comparable to subsidies currently offered in Canada and the US. Fuel costs were calculated from two components unseen to the respondent: fuel price (50-150% of current fuel price) and fuel efficiency (50-120% of current vehicle efficiency). Pollution was presented in exact proportion to fuel efficiency, and thus was not actually included in the utility function. I chose to portray this value to respondents only to communicate the environmental benefits of increased fuel efficiency, which may not have been clear otherwise. Lastly, HEV power ranged from 70% of the respondent’s vehicle (similar to 2005 Toyota Prius) to 115% (attainable by forthcoming models).

Table 6: Attribute Levels in SP Experiment (3^7 Factorial Design)

	Gasoline Vehicle	Hybrid Electric Vehicle (HEV)
Capital Cost (CC) - $	• User CC • 110% User CC • 125% User CC	• 110% User CC • 120% User CC • 150% User CC
Government Subsidy (SUB) - $ Rebate	• No subsidy	• No Subsidy • 5% of HEV CC • 10% of HEV CC
Fuel Efficiency (FE) – L / 100km	• 80% User FE • User FE • 120% User FE	• 50% User FE • 75% User FE • 90% User FE
Pollution (P) - % Difference	• Same As GAS FE %	• Same as HEV FE %
Fuel Price (FP) - $ / L	• 50% User FP • User FP • 150% User FP	• Same as GAS FP
Fuel Cost (FC) - $ / Week	• (User FC) *(GasFE %) *FP%	• (User FC) *(HEV FE%) *FP%
Performance (HP) - Horsepower	• User HP	• 70% User HP • 85% User HP • 115% User HP

In total, this design had seven attributes that varied by three levels, represented as a 3^7 factorial yielding 243 possible choice sets. I have used a function in SPSS to derive a fractional factorial design (Appendix B) that only requires 18 choice sets to be orthogonal.[4] All 18 choice sets were presented to each respondent in the survey. In summary, this experiment was designed to yield the following SP utility function:

$$V_{SP} = \beta_{CC} \cdot CC + \beta_{FC} \cdot FC + \beta_{P} \cdot P + \beta_{SUB} \cdot SUB + ASC_{HEV} \quad \text{Equation 12}$$

[4] An orthogonal factorial design has zero or negligible correlation among attributes, thus avoiding collinearity problems in the specification of choice models.

Where CC is capital cost, FC is fuel cost, P is vehicle power, SUB is government subsidy, and ASC_{HEV} is the constant specific to hybrid-electric vehicles. As noted above, the RP choice model did not include a subsidy coefficient, so the RP utility function is represented as follows:

$$V_{RP} = \beta_{CC} \cdot CC + \beta_{FC} \cdot FC + \beta_{P} \cdot P + ASC_{C} \qquad \text{Equation 13}$$

Where ASC_C is the constant specific to each of the 12 vehicle classes included in the RP choice sets (described in Section 2.2.2).

2.3.3 Information Acceleration Treatment

Because the primary objective of this study was to measure preference dynamics, respondents were divided into three groups and presented with different hypothetical market scenarios. This allowed the estimation of different *i* parameters for each scenario, facilitating the estimation of an intangible cost function using SP data. The three scenarios were set up using a market research technique known as information acceleration, which creates hypothetical scenarios using multimedia stimuli to forecast consumer responses to new technologies (Urban et al., 1997). In one study, scenarios were simulated with hypothetical magazine and newspaper articles, advice from fellow consumers, and even a virtual vehicle showroom to forecast the potential sales of a new electric vehicle (Urban et al., 1996). Previous CIMS research used information acceleration to estimate preference dynamics for HEVs (Mau, 2005) and hydrogen fuel cell vehicles (Eyzaguirre, 2004). Information acceleration is also helpful for controlling for the lurking variables described in the previous section.

The three scenarios in this study described different levels of HEV penetration: 1) current or low market share (0.17% in Canada, 3.0% in California), 2) moderate market share (10%), and 3) high market share (50%). A different information acceleration package was presented to each group, including general details about HEVs, as well as several optional readings: a newspaper article, an advertisement brochure and 2-3 testimonials from strangers, friends, and family. Table 7 summarizes the major differences in information provided to each group.

Table 7: Market Share Treatment Scenarios for SP Experiment

	HEV Model Availability	**Advertising Target**	**Testimonial Sources**
1) 'Current' Scenario 0.17% or 3.0% MS	Only: - Subcompact Car - Compact Car - Small SUV	Innovators: Focus on cutting edge appeal	Friend: Unsure Stranger: Positive
2) 'Moderate' Scenario 10% MS	'Current' Plus: - Midsize Car - Medium SUV - Minivan - Small Pickup	Early Adopters: Concern for Fuel Efficiency and Environment	Friend 1: Unsure Friend 2: Positive Stranger: Positive
3) 'High' Scenario 50% MS	All Models Available	Majority: Financial Savings	Friend 1: Positive Friend 2: Positive Family: Positive

First, the availability of HEV models was restricted in the two lower market share groups. I suspect that model availability is a major explanatory factor in the current market share of HEVs, but is too complex to directly include as a SP model attribute. Because HEV model variety is expected to increase as market share increases, this factor was included as part of the market share treatment. Not only were respondents informed about restrictions in model variety, but they were also asked to select their preferred HEV model type from those available. Their preferred model type was then presented with the other HEV attributes in the SP choice sets.

A hypothetical newspaper article was also made available to respondents, presenting basic information about HEVs (example in Figure 12). Sources like these are considered to be relatively neutral, and have proved useful in previous information acceleration studies (e.g. Urban et al., 1996). I styled the article according to a number of real life HEV newspaper articles and consumer websites. The only major change across the three scenarios was the extent of HEV penetration.

Figure 12: Information Acceleration: Newspaper Article Example

Hybrid Electric Vehicle Sales Booming: 1 out of 10 New Vehicles Sold is a Hybrid
By Suzanne Johnson

Hybrid vehicle sales are continuing to explode.

High gas prices, government regulation and good word-of-mouth are prompting more drivers to buy hybrid cars, which combine gasoline engines with battery-powered electric motors. By the end of last year, nearly 1 out of every 10 new vehicles sold was a hybrid. This means that most city-dwellers have a neighbour that owns a hybrid.

Hybrid vehicles are good for the earth because they suck up less gas and spit out less pollution. Likewise, hybrids are also good for our wallets -- they can cut the gas bill by up to one half, and are often eligible for government subsidies.

The hybrid's popularity has also been helped by the growing variety of models available. In addition to cars, hybridized versions of the SUV and minivan are now available, appealing to a whole new market of families and workers.

However, being an environmental trailblazer isn't cheap. Hybrid cars can cost substantially more than comparable conventional cars. Despite ultra-impressive gas mileage, hybrid owners may have a tough time making up the price difference at the pump.

Cities across the country have been grappling with the challenges of poor air quality and growing emissions of global warming gases. Driving a hybrid-electric vehicle may be one way to help out, which is why the government is promoting this technology.

The age of the hybrid vehicle may be upon us. We can see them on nearly every block, and in time hybrids may prove to dominate the market

In addition, an advertising brochure was provided that varied significantly among market scenarios (example in Figure 13). It was assumed that marketers would tailor advertisements to the stage of product diffusion in each scenario, according to the diffusion of innovations theory (Rogers, 2003). In the low market group, the advertisement targeted innovators by emphasizing the cutting edge nature of HEV technology. In the moderate scenario, marketers targeted a broader market (early adopters) by focusing on both fuel savings and environmental friendliness. The high market share brochure targeted the majority of consumers, focusing almost exclusively on financial savings. Thus, as market share increases, marketing efforts are assumed to progress from a quality focus to a financial focus. I styled the brochures according to HEV advertisements produced by Honda and Toyota.

Figure 13: Information Acceleration: Advertisement Example

Hybrid Electric Vehicles: Welcome to the Future

Introducing our new hybrid electric vehicles, the cutting-edge of transportation. Our Hybrids replace convention with fresh thinking and innovative design.

Our hybrid electric vehicles use technology with a conscience. The gas/electric hybrid engine is exceptionally efficient, cutting pollution while saving you money. It is the easy way to help reduce air pollution and avoid climate change. Plus you spend half as much time and money at the fuel pump

The hybrid is everything a vehicle should be: powerful, responsive, accommodating, safe, and reliable. All this, and you never have to plug it in for recharging. If you want to make a difference in your environment and pocketbook, visit your local dealership.

Finally, the product testimonials presented to each group primarily varied by the degree of certainty communicated (example in Figure 14). Generally, consumer uncertainty about a product is higher when the product is newer (Hoeffler, 2003). I styled testimonials according to real-life HEV websites that present consumer reviews. The low market share scenario presented less information (only two testimonials), from sources that had less direct experience with HEVs and thus communicated more uncertainty. The moderate market share testimonials included sources that had direct experience with HEVs and more positive feedback. The high market share scenario presented testimonials from friends and family as credible sources.

Figure 14: Information Acceleration: Testimonial Example

Friend 1: "I've heard a lot about hybrid cars, and I'm not so sure about them"

I haven't been in a hybrid car yet, but I've heard a lot about them. They sound pretty interesting. I think it's a cool idea to combine a gasoline and electric car. From what I heard, you get a very quiet ride, and the engine turns off when you stop. So its supposed to be way more fuel efficient, and put out less exhaust. So it seems like a good deal for the environment, but you do have to pay extra for it.

I'm not so sure about the car's performance though. How could it be as powerful with a smaller gasoline engine? And you know how technologies are, the more complicated they get, the more that can go wrong. And if you want a big, safe vehicle, good luck! I've only seen small hybrid cars. I'm sure you would have problems getting bullied by bigger cars on the road.

Apparently they are catching on though, something like 1 out of every 10 new cars sold is a hybrid. I don't think I'm sold though.

2.3.4 Presenting the Choice Sets

Following the information treatment, respondents were presented with 18 hypothetical choices sets. To stimulate cognitive effort in this task, respondents were asked to perform a 'mental simulation' exercise, where they reported the details of a typical route they would drive with their primary vehicle. Respondents were instructed to keep this visualization in mind when considering each of the choice sets, imagining the feeling of driving each of the presented vehicle alternatives along this route. Such mental simulation exercises have been established as useful tools for encouraging realistic product adoption decisions (Hoeffler, 2003).

Each choice set presented two options: one conventional gasoline vehicle, and one HEV. Each option specified the class, purchase price, weekly fuel cost, pollution level, subsidy and performance of the vehicle. The class of each vehicle was specified by the user in the previous section, accompanied by a simple neutral picture to aid in the realism of the choice set (Figure 15). Purchase price was presented as a retail value, excluding tax or subsidy. The fuel cost was presented as a weekly value, calculated from fuel efficiency and fuel price (which were not shown). As previously discussed, pollution was presented as a proportion inverse to fuel efficiency level. Subsidy was presented as a rebate received by the respondent six months after purchase. Lastly, car performance was presented as a percentage change from the respondents' primary vehicle. For those respondents that could report the horsepower of their primary vehicle, the corresponding horsepower value was presented in brackets. Respondents were instructed to click on any of the attributes to get a more detailed description. Table 8 portrays a sample choice set.

Figure 15: Vehicle Class Images

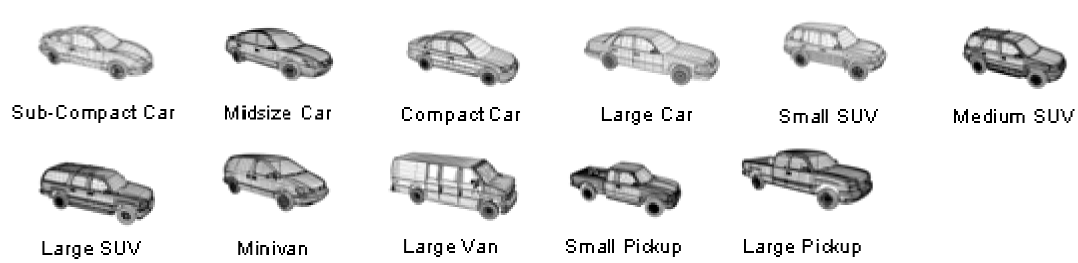


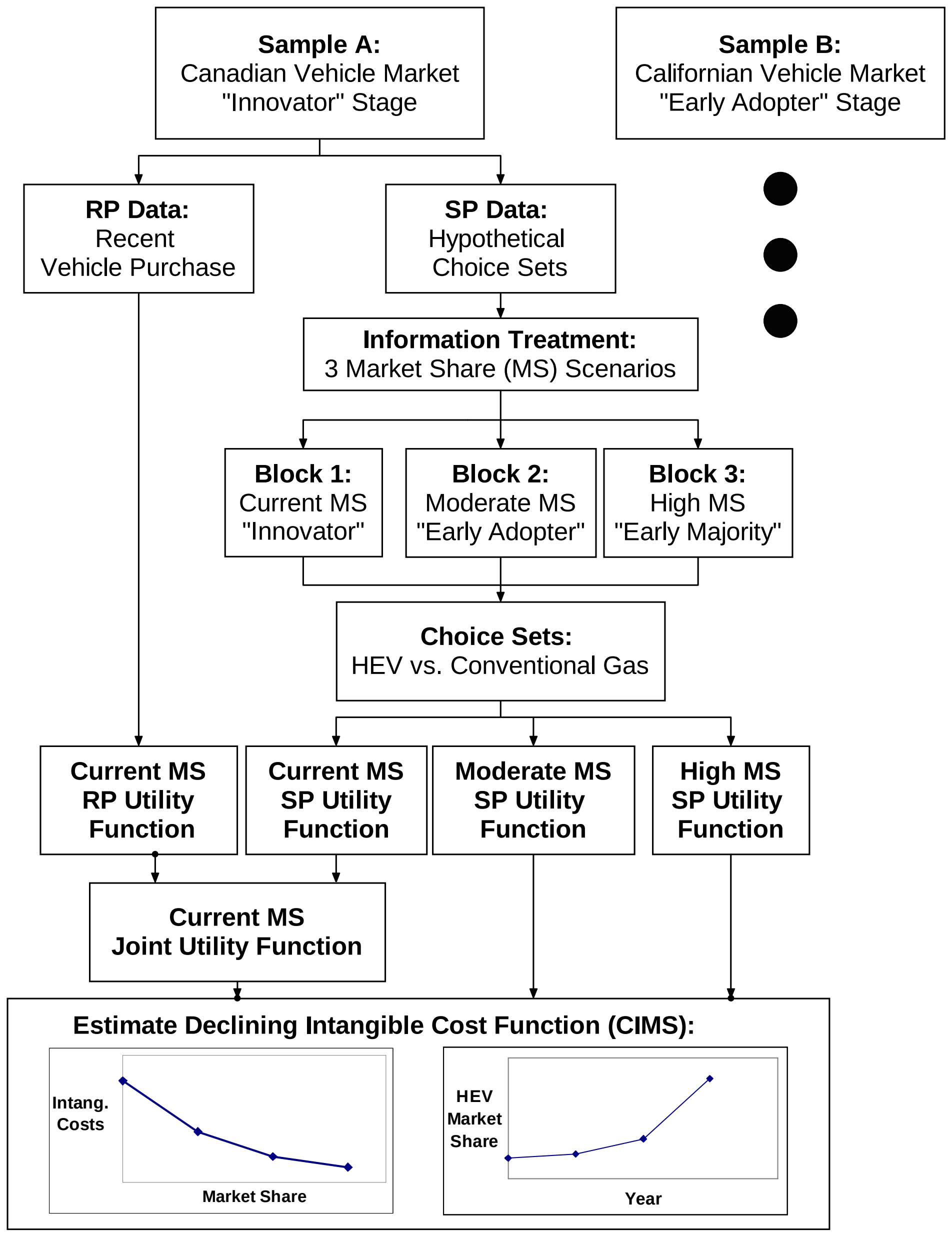
Table 8: **Sample Choice Set**

	 **Medium SUV Gasoline Vehicle**	 **Small SUV Hybrid Electric Vehicle**
Purchase Price (Excluding tax or subsidy)	$27,500	$35,000
Fuel Cost/Week	$35	$26
Pollution	Same as Current Vehicle	25% Less than Current Vehicle
Subsidy on Purchase Price (Provided by Government 6 months after purchase)	No Subsidy	$3,500
Car Performance (Measured in horsepower of vehicle engine)	Same as Current Vehicle (150 HP)	15% Better Than Current Vehicle (172 HP)
I Choose:	□	□

2.3.5 Integration of SP Experiment with RP Model

Figure 16 presents a visual summary of the experimental design of this study. The Canada and California samples collected both SP and RP data. Utility functions were estimated from RP data using attributes drawn from a comprehensive vehicle database. The SP data was divided into three hypothetical market share groups using information acceleration techniques. To improve choice model realism, joint SP-RP models were estimated from the RP data and SP ‘current’ scenario. The same procedure was conducting with California data. The resulting choice models were used to estimate the declining intangible cost function and other behavioural parameters to improve the realism of market share forecasts produced by CIMS.

Figure 16: Experimental Design Flow Diagram



2.4 Incorporating Uncertainty

Inevitably, there were many sources of uncertainty in the parameters estimated in this study, such as preference heterogeneity and potential model misspecification. To present any parameter estimate as only a single point ignores this uncertainty, and is arguably a misleading and inappropriate practice, particularly given the intention of this study to help inform policymakers about the likely outcomes of their policies. Morgan and Henrion (1990) discuss how uncertainty analysis can help identify causes of uncertainty, provide guidance for future studies, and also aid in the comparison of different predictions by presenting ranges of outcomes instead of single estimates. Looking specifically at choice models, uncertainty strategies can help increase the economic integrity of estimated models, more thoroughly communicating the robustness of results (Layton & Lee, 2006). For these reasons, I have conducted uncertainty analyses for the choice model coefficients, CIMS behavioural parameters, and CIMS policy simulation outputs estimated in this study. I have taken three different uncertainty analysis approaches in this study: Bayesian conditional probability distributions, Monte Carlo simulation, and sensitivity analysis.

2.4.1 Bayesian Probabilities: Choice Model Coefficients

A Bayesian approach was followed to investigate the uncertainty in choice models coefficients. This approach is helpful for presenting uncertainty, as it is assumes that parameter estimates are not deterministic, but rather the most probable of a distribution of possible values. The probability for each value of the distribution, or 'posterior' probability, is estimated from two sources: the likelihood value calculated from the data, and the prior distribution determined by the researcher from previous research or opinion. In this study, the likelihood value was calculated as the proportion of consumer choices observed in the data that match the 'ideal' choice as predicted by the choice model. The prior distributions were 'uninformed' in this study, meaning that no previous data was used to influence the posterior probability estimates, represented as a uniform distribution.

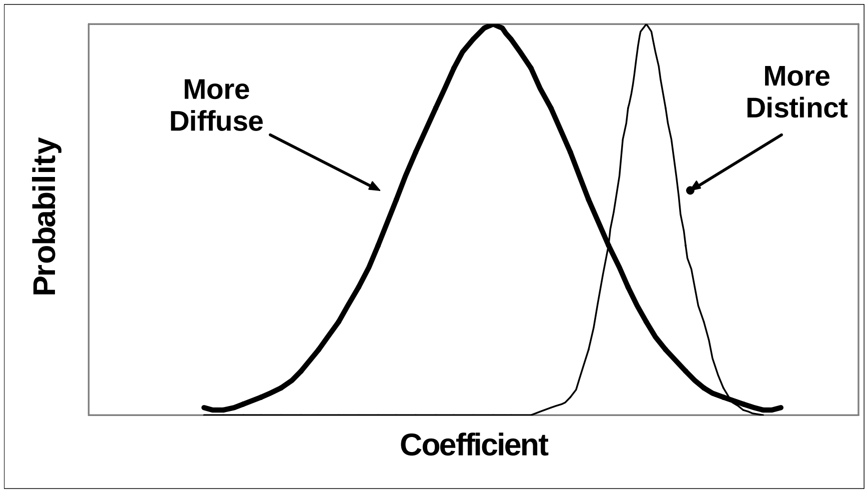
In the Bayesian approach, the probability of a parameter taking on a given value, *i*, can be represented as a hypothesis, *h*, that is conditional upon the data. The probability of each hypothesis, given the data, is equivalent to the ratio of the likelihoods, *L*, of the observed data. This is depicted in the following function:

$$P_{(h|data)} = \frac{L_{(data|h_j)}}{\sum_{k=1}^{K} L_{(data|h_k)}} \qquad \text{Equation 14}$$

Where *K* represents all other theoretical values of the parameter in the utility function. When the posterior probabilities are compiled for a given range of hypothesis values, the resulting distribution function helps assess the certainty of the parameter's most likely estimate. Two hypothetical posterior probability distribution functions are depicted in Figure 17. Relatively speaking, the wider distribution is more 'diffuse', with a higher degree of uncertainty than the narrower, 'distinct' distribution. Note that the heights of the two distributions are scaled differently to facilitate comparison, as the area under each distribution should be equal.

It has been found that uncertainty is more easily communicated to the layperson using this type of Bayesian method, compared to a classical statistical approach. Also, Bayesian methods are better suited than classical methods for comparing the relative uncertainty of different models because posterior probability distributions provide a more complete representation of how well each model fits the data (Wade, 2000). Thus, this procedure was particularly useful for comparing the certainty of coefficients in the SP, RP and joint models.

Figure 17: Comparing Hypothetical Probability Distributions (Scaled)



2.4.2 Monte Carlo Simulation: CIMS Parameters

Uncertainty in each CIMS behavioural parameter in this study results from uncertainty in the choice coefficients used to calculate these parameters. Monte Carlo simulation is a well-established, and relatively straightforward method of determining probability distributions for parameters that depend on other uncertain parameters (Morgan & Henrion, 1990). Therefore, this method was useful for estimating uncertainty in the *r* and *i* parameters from uncertainty in the capital cost, fuel cost, and non-monetary attribute coefficients of the choice models. I first specified the probability distribution of each input coefficient, then performed a Monte Carlo simulation of 10,000 runs. Each run randomly selects input coefficients according to the specified distributions, then records the resulting output parameter estimate. The distributions of these outputs portrayed uncertainty in the behavioural parameters.

In this study, I have used the simulation software package Crystal Ball to conduct Monte Carlo simulations for each behavioural parameter. Despite the merits of the Bayesian approach described in the previous section, I have defined the input coefficients according to classically derived distributions, assumed to follow normal distributions according to the standard errors of the choice models. This approach allowed me to correlate the random draws of different coefficients, according to the correlations observed in responses to attributes. Crystal Ball has a function that allows the specification of coefficient correlations, which I derived from the covariance matrices produced in choice model estimation. Also, this classical approach is more objective than the Bayesian approach, as the probability ranges of each coefficient were determined by the model outputs, not subjective judgment.

2.4.3 Sensitivity Analysis: CIMS Forecasts

The CIMS model was not designed to present uncertainty in simulation forecasts. Due to this limitation, and the time constraints involved in running CIMS, I have translated uncertainty estimates in the previous two exercises into CIMS through a sensitivity analysis. Sensitivity analysis is a method of computing how changes in the input (behavioural parameters) affect model predictions (Morgan & Henrion, 1990). The probability densities calculated through Monte Carlo simulation provide an understanding of reasonably high and low parameter estimates. I conducted simulations in CIMS with three versions of each behavioural parameter: the maximum likelihood estimate (MLE), and the high and low end points (or tails) of a specified interval. This procedure tested the sensitivity of CIMS market share forecasts to uncertainty in coefficient estimates. If forecasts did not change substantially, CIMS is considered not to be very sensitive to uncertainty in that particular parameter, improving confidence in the forecasts. However, if sensitivity is high, CIMS forecasts are viewed with less confidence. These results must be kept in consideration when making policy recommendations from simulation forecasts. Sensitivity analysis also helped to identify important problem areas in a model, which may require further investigation.

CHAPTER 3: CHOICE MODEL RESULTS

This chapter analyzes the stated (SP) and revealed preference (RP) data collected with the online survey described in the previous chapter, using several choice modelling techniques. The first section investigates the external validity of the Canada and California samples, that is, how well the samples represent the target populations. The following two sections describe and assess choice models derived from SP and RP data, respectively. The fourth section details the estimation of a joint SP-RP model, using the 'best' of the SP and RP-only models. Finally, the fifth section presents an uncertainty analysis of the choice model coefficients and market share predictions, comparing the certainty of the three estimation procedures. The ultimate objective of this process was to select optimal choice models to use as inputs into behavioural parameters calculated for CIMS.

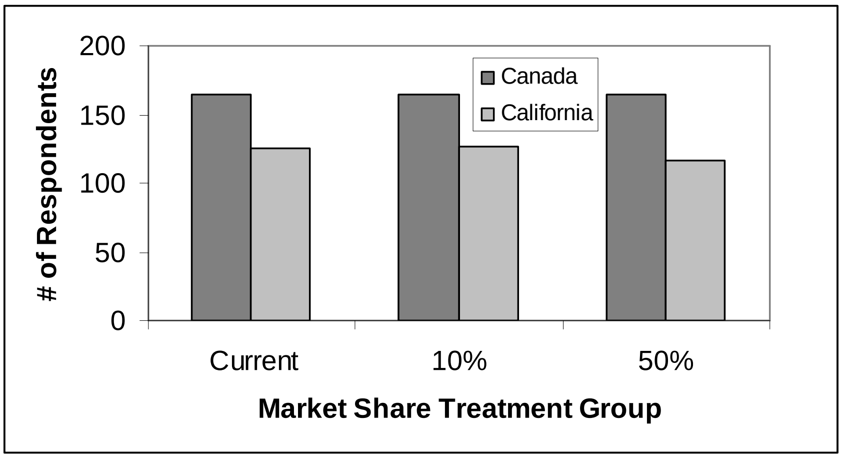
3.1 Population Samples

The Canada and California samples were recruited according to the strategy outlined in Section 2.3.1, targeting recent purchasers of new vehicles. Hybrid electric vehicle (HEV) owners were purposely overrepresented using a choice-based sampling strategy. The final breakdown of respondents (after removing problematic responses) was 544 Canadians (51 HEV owners) and 422 Californians (54 HEV owners). These figures are presented in Table 9 along with the sample targets described in Section 2.3.1. All target sizes were surpassed.

Table 9: **Sample Breakdown of Respondents by Region and Vehicle Type (Target in Brackets)**

	Canada	California	TOTAL
Conventional Gasoline Vehicle Owners	**493** (450)	**368** (150)	**861** (600)
Hybrid Electric Vehicles Owners	**51** (50)	**54** (50)	**105** (100)
TOTAL	**544** (500)	**422** (200)	**966** (700)

Figure 18: Respondents Per Market Share Treatment



For the SP choice experiment, survey respondents were randomly assigned to one of three market share treatment groups. The resulting distribution was nearly equal across groups (Figure 18). Respondents completed 18 SP choice sets, yielding nearly 3000 choice observations per Canada treatment group, and 2200 per California treatment group. HEV owners were excluded from the main SP experiment, as they were recruited solely for the RP models. The choice responses of HEV owners could have been included in the SP models if they were weighted to counter the choice-based sampling technique.

However, the models resulting from this procedure are no different from models excluding HEV owners.[5] I opted to exclude HEV owners to simplify the process.

In survey research, it is common practice to report a survey's response rate, that is, the proportion of sampled individuals that completed the survey. Response rates are used as a simple indicator of sample quality, representing the degree of bias that may be introduced to survey results by a self-selecting sample. This figure is not applicable to this study because respondents were pre-recruited from consumer panels maintained by market research firms, not randomly sampled from the general population. This panel-based strategy was still susceptible to selection bias, so it was important to assess sample quality with other indicators. The next two sections describe several methods of investigating the external validity of the Canada and California samples.

3.1.1 Validity of Canada Sample

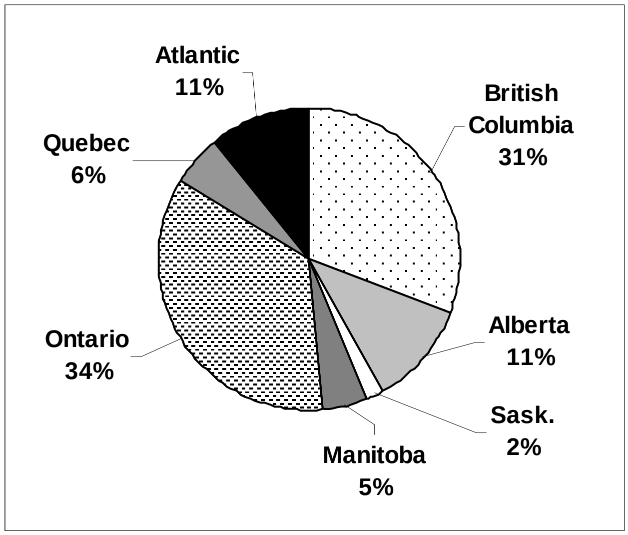
The primary objective of this study was to estimate consumer preference dynamics in the Canadian economy. Thus, it was important that the samples used to derive behavioural parameters were representative of the Canadian population. To assess the validity of generalizing the results of this study, I compared the Canada sample with 2001 Canadian Census data, focusing on six key demographic variables: population, gender, age, income, education, and type of vehicle owned. I provide a summary here, while the full results are depicted in Appendix C.

Population: the distribution of respondents by province/region (Figure 19) was very close to the actual population measured in the 2001 Census. There are two

[5] The responses of HEV owners were given such a small weight that they could not significantly affect the coefficients estimated by the model.

exceptions. First, BC was substantially overrepresented, likely because recruitment was based from Vancouver. Secondly, Quebec was substantially underrepresented because the survey was not made available in French.

Figure 19: Respondent Breakdown by Province of Residence



Gender: females were slightly overrepresented, a trend that is observed in previous studies of this nature (e.g. Mau, 2005).

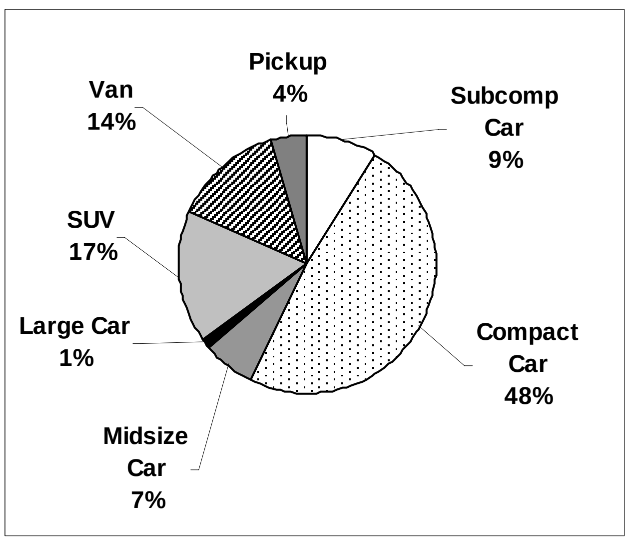
Age: ages 20-50 were slightly overrepresented in the sample relative to the population, though I suspect this is representative of new vehicle buyers.

Income: the income distribution was biased towards a higher household median ($79,000) than that indicated by census data ($72,000). Again, this difference may be appropriate because new vehicle buyers likely have relatively higher income levels.

Education: the sample was skewed towards higher education, with nearly double the number of university graduates (61%) compared to census data (33%). This bias is likely a result of conducting a web-based survey, which tends to recruit more educated, computer savvy respondents. Because education and environmental awareness could be correlated, the survey may have overrepresented consumers with preferences for environmental technologies. However, it is also likely that university graduates are more likely to purchase new vehicles, so this overrepresentation may be fair.

Vehicle Ownership: the distribution of vehicle classes owned by respondents (Figure 20) is representative of the current Canadian vehicle population. The split between light-duty cars (65%) and trucks (35%) is nearly equal to Environment Canada's estimate (Environment Canada, 2004).

Figure 20: Respondent Breakdown by 'Primary' Vehicle Class Ownership



In summary, the sample of Canadian respondents recruited in this study appeared to be a reasonable representation of Canadian vehicle consumers. The differences in demographic distributions were slight, and most could be explained. Thus, I concluded it was reasonable to use this data to inform a model simulating the Canadian economy. The next section explores the validity of the California sample.

3.1.2 Validity of California Sample

As described in the experimental design section, the primary purpose of recruiting the California sample was to estimate the intangible cost curve for Canada using RP data. Thus, I was not concerned with how well the California sample represented the California population, but instead with how appropriate it was to extrapolate California model results to the Canadian economy. In this sense, external validity refers to how well the California sample represented Canadian vehicle consumers. Fortunately, a comparison of the demographic and attitudinal data of the Canada and California samples indicated a high degree of consistency (details in Appendices C and D).

First, the demographic distributions of the California sample were very similar to the Canada sample, including distribution of income, gender and household size. However, there are several differences: the California sample on average was slightly older, less educated, and more likely to live alone (and purchase vehicles alone). In terms of vehicle ownership, the Californian respondents were more likely to own multiple vehicles, and these vehicles were more likely to include midsize cars, large cars, SUVs, and pickup trucks. However, the California split between light-duty cars and trucks was nearly identical to the Canada sample.

Second, the survey also collected attitudinal data to facilitate the comparison of regional samples. Respondents indicated their level of agreement with 15 statements covering three attitude categories: technology, environment, and government. A five-point Likert scale was used, ranging from strongly disagree to strongly agree. In general, Canadian and Californian respondents scored very similarly on these attitudinal questions (full results provided in the Appendix D). The distribution of agreement was nearly identical for all technology statements (e.g. "New technologies cause more problems than they solve") and most environmental statements (e.g. "I rarely ever worry about the effects of pollution on myself and family"). However, one environmental statement, and several government statements yielded slight differences in agreement. These differences indicated that California respondents were less concerned about climate change, less trusting in government communications about the environment, and less supportive of environmental policies that promote low-emissions technologies.

In summary, the demographic and attitudinal differences observed between Canadian and Californian respondents appeared to be minimal, but were not subject to rigorous statistical analysis. It was difficult to tell whether these differences resulted from sampling error or genuine differences between the target populations. Determining the source of these differences was beyond the scope of this project. Generally speaking, the two samples had far more similarities than differences, and the remainder of my analysis assumed that models derived from the California sample could be reasonably generalized to the Canadian population.

3.2 Stated Preference (SP) Experiment

After assessing the validity of the survey samples, I proceeded to estimate choice models from the collected SP data. The SP choice models are presented here in five stages: 1) assessing the quality of choice observations, 2) estimating the SP models, 3) investigating the appropriateness of model specifications, 4) comparing market share treatment groups, and 5) including demographic variables.

3.2.1 Quality of Responses

I assessed the quality of SP data elicited in each of the six market share treatment groups (MS1, MS2, MS3 for both Canada and California). This procedure helped to highlight problematic models and explain cross-model differences. I utilized four indicators: the proportion of respondents choosing only one alternative, the average time spent completing the survey, the average time spent viewing the information acceleration treatment, and the distribution of choices across the 18 choice sets.

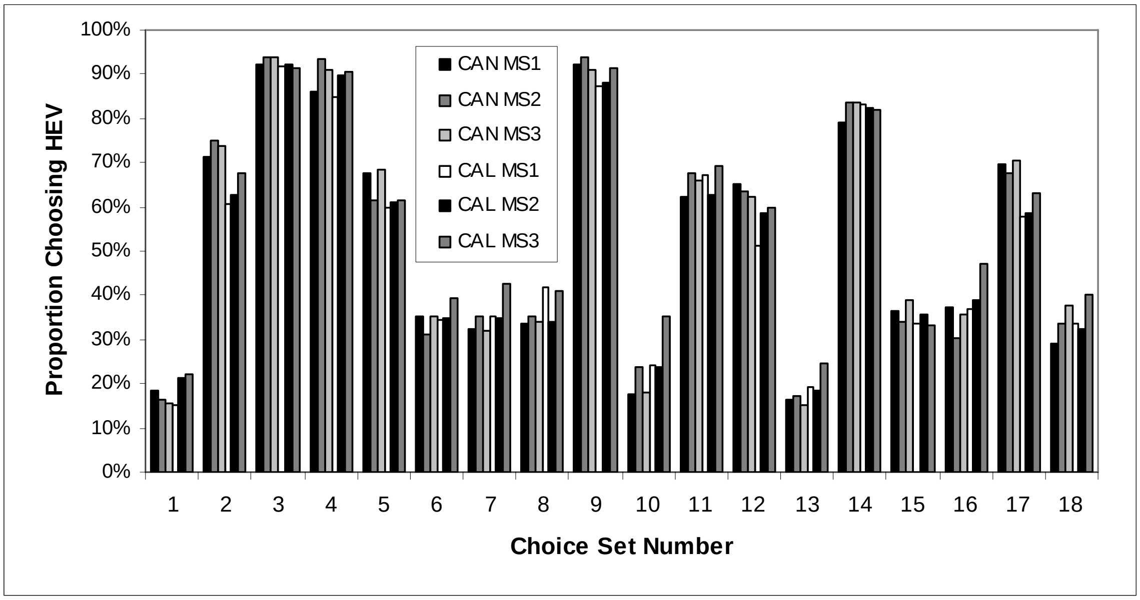
First, the quality of the SP experiment would be considered low if a substantial proportion of respondents consistently chose only one vehicle type (HEV or conventional) for all 18 choice sets. Such a trend would indicate that either the specified attributes were not appropriate, the attribute levels did not vary enough to elicit trade-offs among respondents, or respondents did not spend much time assessing the choice descriptions. This proportion was reasonably low for this study, with an overall average of 8%, varying from a low of 5% (Canada MS1) to a high of 14% (California MS1).

Second, the time spent by each respondent in completing the survey also indicated the quality of collected results. Pre-survey analysis indicated that 15-25 minutes would be required to thoroughly complete the survey. Respondents in the final study spent an average of 23 minutes completing the survey, ranging from 21 (California MS2) to 26 (California MS3) minutes across treatment groups. The proportion of 'quick' respondents, those spending less than 10 minutes on the survey, was reasonably low with an average of 9%, ranging from 4% (Canada MS2) to 16% (California MS1).

Third, I also measured the time each respondent dedicated to the "information acceleration" exercise, which was an integral part of the SP experiment. On average, respondents spent 2.5 minutes viewing the presented information, ranging from 1.75 minutes (California MS1) to 3.5 minutes (Canada MS1). This range was consistent with pre-survey estimates. On average, 14% of respondents spent less than 30 seconds viewing this information, ranging from a low of 10% (Canada MS1) to a high of 22% (California MS1).

The final indicator of choice quality I assessed was the distribution of choices among the 18 choice sets. Systematic variation in the proportion of vehicles chosen among the choice sets indicated that attribute and attribute levels were appropriately specified to influence respondents. Figure 21 shows clear patterns of choice proportion among the 18 choice sets which were fairly consistent for all 6 sample groups. Also note that neither vehicle type was chosen less than 10% or more than 95% of the time, indicating that trade-off points were observed for all choice sets.

Figure 21: Frequency Distribution of HEV Choices in SP Experiment



In summary, the quality of SP responses was reasonably high, with no reason to expect difficulties in the modelling stage. However, there were substantial quality differences between sample groups. The California groups (particularly MS1) were consistently ranked lower on quality indicators than Canada groups, such as the number of 'quick' respondents. This quality discrepancy likely stems from the different recruitment strategies employed for each sample, where relatively more time and resources were intentionally dedicated to recruiting the Canada groups.

3.2.2 Canada Choice Models

Next, I estimated SP choice models according to the multinomial logit (MNL) methodology described in Section 2.1.2. The results for the three Canada market share treatment groups are portrayed in Table 10. All three models appear to be reasonably specified, according to three basic indicators. First, each coefficient is of the expected sign. In other words, attributes associated with negative utility, such as capital and fuel cost, have negative coefficients. Secondly, all coefficients are highly significant, as indicated by high t-values. The t-values indicate that each attribute coefficient (or explanatory variable) is significantly different from zero at a 99% confidence level. Thus, each coefficient adds to the explanatory power of each model. A third indicator is the chi-square value, which tests if the choice model is statistically superior to a 'base' version of the model without any coefficients. All three models pass this test at a 99% confidence level. The log-likelihood ratio is sometimes reported as another key indicator, known as the pseudo-R^2. This ratio is uninformative in absolute terms, but can help in comparing the explanatory power of different models. The three SP models in Table 10 have similar log-likelihood ratio values.

Table 10: Canada SP Choice Models - Three Market Share Treatment Groups

	Market Share 1 0.17%		**Market Share 2 10%**		**Market Share 3 50%**	
Attribute	**Coeff**	**t-Value**	**Coeff**	**t-Value**	**Coeff**	**t-Value**
Capital Cost	-0.000141	-16.61 (0.00)	-0.000151	-18.41 (0.00)	-0.000158	-18.74 (0.00)
Fuel Cost	-0.0298	-11.28 (0.00)	-0.0342	-11.72 (0.00)	-0.0403	-13.29 (0.00)
Subsidy	0.000101	3.67 (0.00)	0.000144	5.58 (0.00)	0.0000721	2.71 (0.01)
Power	0.00871	6.70 (0.00)	0.0144	10.82 (0.00)	0.0117	8.62 (0.00)
HEV ASC	0.261	3.71 (0.00)	0.465	6.39 (0.00)	0.527	7.25 (0.00)
# of Obs	2952		2952		2970	
Chi-Square	480.12 (0.00)		632.86 (0.00)		651.59 (0.00)	
LL	-1802.88		-1714.06		-1712.42	
LL (No coeff)	-2046.17		-2046.17		-2058.65	
LL (ASC only)	-2042.94		-2030.48		-2038.21	
LL ratio	0.118		0.162		0.168	

Notes: p-values in brackets, LL refers to the Log Likelihood of the model, which are also shown for models specified with no coefficients and constants only for comparison.

The coefficient values in Table 10 are consistent across all three treatment groups. To facilitate a more intuitive assessment, monetized versions of the coefficients are portrayed in Table 11. An attribute coefficient can be monetized through division by the capital cost coefficient. This specification frames each attribute as a trade-off with purchase price, that is, the extra dollars a consumer is willing to pay in purchase price to get an extra unit of a positive attribute, or one less unit of a negative attribute. For example, the average respondent in MS1 would pay an extra $62 in purchase price for a vehicle with one extra unit of horsepower, all else held constant. Likewise, MS1 respondents would pay a premium of $1,851 for a HEV, relative to a conventional vehicle with otherwise equivalent attributes.

Table 11: Monetized SP Coefficients (Canada)

	MS 1 - 0.17%	MS 2 - 10%	MS 3 -50%
Attribute	**$ Value**	**$ Value**	**$ Value**
Fuel Cost (per $/week reduced)	$212	$227	$256
Subsidy (per extra dollar)	$0.71	$0.96	$0.46
Power (Per extra unit horsepower)	$62	$95	$74
Hybrid Constant (Premium for HEV)	$1,851	$3,088	$3,354

The monetized coefficients are comparable to those calculated in previous studies. The fuel cost values are very close to those estimated by Mau (2005). On the other hand, the subsidy attribute indicates that $1 of subsidy is worth only $0.46-$0.96 of capital cost savings, which contrasts with Mau's finding that subsidies were valued proportionally higher than capital cost. This low valuation of subsidies could be explained by the negative utility of the 6-month rebate delay, general opposition to subsidy programs, or modelling error.[6] Next, the power coefficient is similar to Ewing and Sarigollu's (2000) vehicle choice model, as both equate a loss of 20 hp with $2500-$3500 of purchase price. The $1,851 hybrid premium in the low market share model is considerably lower than Ewing and Sarigollu's estimate of $5,600 for alternative vehicles. However, the hybrid premiums across the three market shares are similar to those calculated by Mau.

The coefficients can also be interpreted as the importance each attribute contributes to the total utility of a given vehicle. Table 12 presents the attributes assigned to the 'generic' conventional vehicle and HEV throughout this study, derived from the 2006 Honda Civic and Civic Hybrid specifications in the vehicle database. For instance, the conventional Honda Civic is assumed to have a purchase price of $22,729, a weekly fuel cost of $20, no subsidy, and a 127 horsepower engine. These Honda models were chosen for two reasons: 1) subcompact cars make up nearly 50% of total passenger vehicle sales, and 2) other than hybridization, the two models are very similar. The utility derived from each attribute of the Civic HEV is presented in Figure 22. In each market share scenario, capital cost is the dominant factor, followed by power, fuel cost, the HEV constant, and subsidy. Attribute importance is perhaps better measured as contribution to *relative* utility, the difference in utility between the two vehicles. Figure 23 portrays the contribution of each attribute to the utility difference between the Civic and its hybridized counterpart (positive and negative utility are not distinguished). For instance, the difference in capital cost explains about 35-42% of the utility differences between the conventional and HEV Civics, while fuel cost explains 6-12%, and a $1500 subsidy

[6] The 6-month subsidy delay was communicated in the survey choice sets, as most subsidies are realized as rebates or tax breaks, which take around 6-months on average to receive.

would explain 3-6% of difference. Note that in this illustration, the two non-monetary attributes (power and HEV constant) contribute 35-45% of total relative utility. Thus, intangible costs explain more than one third of the consumer choice process in these models.

Table 12: 2006 Honda Civic and Civic Hybrid Vehicle Attributes

	2006 Honda Civic	
	Conventional	**HEV**
Capital Cost	$22,729	$28,000
Weekly Fuel Cost	$20	$13.4
Subsidy	-	$1500
Horsepower	127	93
Hybrid Constant	0	1

Figure 22: Attribute Contribution to *Total* Utility – 2006 Honda Civic HEV

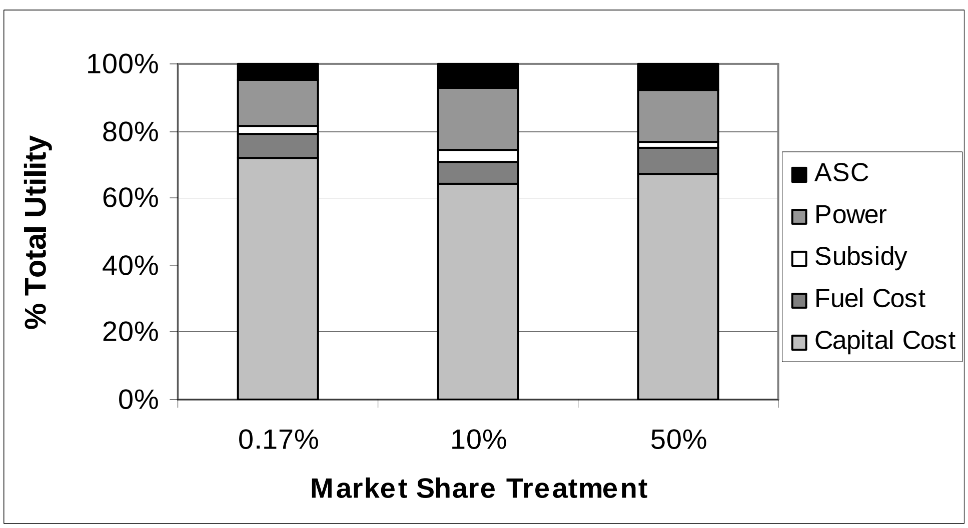
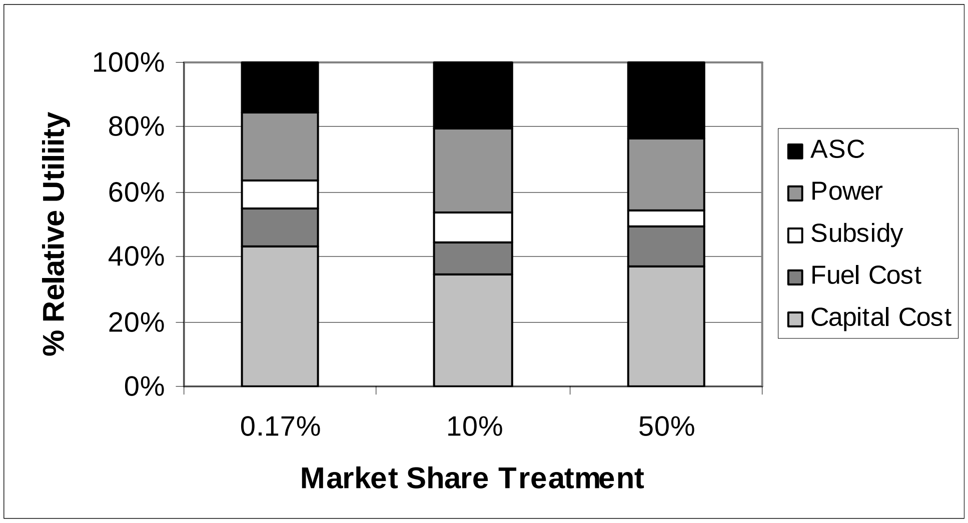


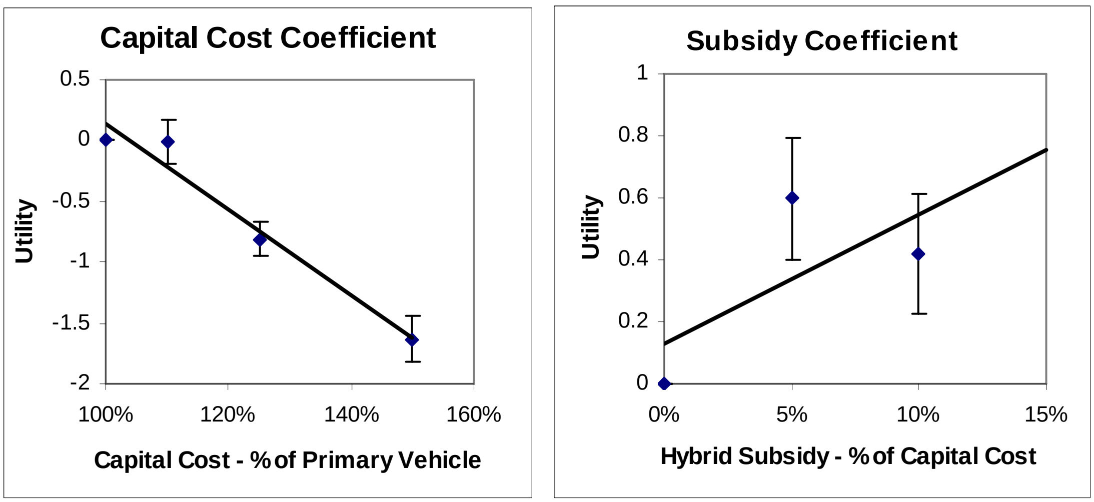
Figure 23: Attribute Contribution to *Relative* Utility – 2006 Honda Civic Vs. Civic HEV



The final analysis presented in this section examined the assumption of linearity in the choice model specifications. All three models in Table 10 assumed a linear relationship between the attribute level and perceived utility (except the *ASC*). However, economic theory suggests that additional utility tends to decrease with each additional unit of a good, known as the law of diminishing marginal utility. This tendency is a result of human perception, where a change in subsidy from \$0 to \$500 is greeted with more enthusiasm than a subsidy increase from \$5000 to \$5500. I have tested linearity assumptions in this model by redefining each attribute as a categorical or quadratic variable. Categorical variables are specified as discrete categories (e.g. high, medium and low) as opposed to a continuous value (e.g. capital cost). By redefining a continuous variable as a series of categories, the resulting plot of coefficients reveals if an assumption of linearity is reasonable. Figure 24 illustrates this process, where the capital cost and subsidy attributes were transformed into categorical variables. A line was fit to the resulting coefficients, along with whiskers indicating 95% confidence intervals.

Linear variables were also tested using a quadratic form, which allows utility to change at different rates at different attribute levels (account for such factors as diminishing marginal utility).

Figure 24: Part-Worth Utility of Capital Cost and Subsidy Coefficients



This test was performed on all four attribute coefficients. Both the capital cost and power coefficients were determined to fit a linear specification quite well. However, the linear specifications of subsidy and fuel cost attributes were found to be less appropriate. When specified categorically, the subsidy attribute was valued higher at a 5% level than a 10% level, a result that does not make economic sense. In addition, the fuel cost attribute was found to be better specified as a quadratic variable, which statistically improved the overall model. Overall, however, I consider the implications of these misspecifications to be minor. Re-specification of the subsidy coefficient does not improve the model. The quadratic specification of fuel cost would greatly complicate the model, particularly for the estimation of joint models and CIMS behavioural parameters. Thus, I maintained the assumption of linearity for each coefficient in the remainder of the study.

3.2.3 California Choice Models

Choice models were also estimated using the California SP data. These models were not intended to inform CIMS parameters directly, so a less detailed analysis is presented here. The models are summarized in Table 13. Like the Canada models, the California SP models are highly significant, with coefficients that are of the expected sign and mostly significant at a 99% confidence level. However, the subsidy coefficient is an exception in all three models, taking on unexpectedly low, statistically insignificant values. All other monetized coefficients (Table 14) produce similar ranges to those in the Canada models (Table 11) for fuel cost ($226-$232), power ($66-$115) and the hybrid constant ($1,745-$4,168). The observed difference in subsidy valuation could be explained by the attitudinal differences of Californians described in Section 3.1.2, such as higher resistance to government involvement in environmental issues. On the other hand, the California data was also found to be of lower quality than the Canada data, which could have influenced results.

Table 13: California SP Choice Models - Three Market Share Treatment Groups

	Market Share 1 3%		Market Share 2 10%		Market Share 3 50%	
Attribute	**Coeff**	**t-Value**	**Coeff**	**t-Value**	**Coeff**	**t-Value**
Capital Cost	-0.000126	-12.36 (0.00)	-0.000193	-16.48 (0.00)	-0.000184	-16.21 (0.00)
Fuel Cost	-0.0285	-8.13 (0.00)	-0.0448	-11.53 (0.00)	-0.0420	-9.83 (0.00)
Subsidy	0.0000719	2.19 (0.03)	0.0000496	1.44 (0.15)	0.0000414	1.18 (0.24)
Power	0.0146	11.08 (0.00)	0.0159	11.31 (0.00)	0.0123	8.62 (0.00)
HEV ASC	0.458	5.80 (0.00)	0.337	4.04 (0.00)	0.769	8.80 (0.00)
# of Obs	2250		2268		2106	
LL	-1383.20		-1278.62		-1199.09	
LL (No coeff)	-1559.58		-1572.06		-1459.77	
LL (ASC only)	-1556.05		-1570.27		-1439.74	
LL ratio	0.113		0.187		0.179	

Notes: p-values in brackets, LL refers to the Log Likelihood of the model, which are also shown for models specified with no coefficients and constants only for comparison.

Table 14: Monetized SP Coefficients (California)

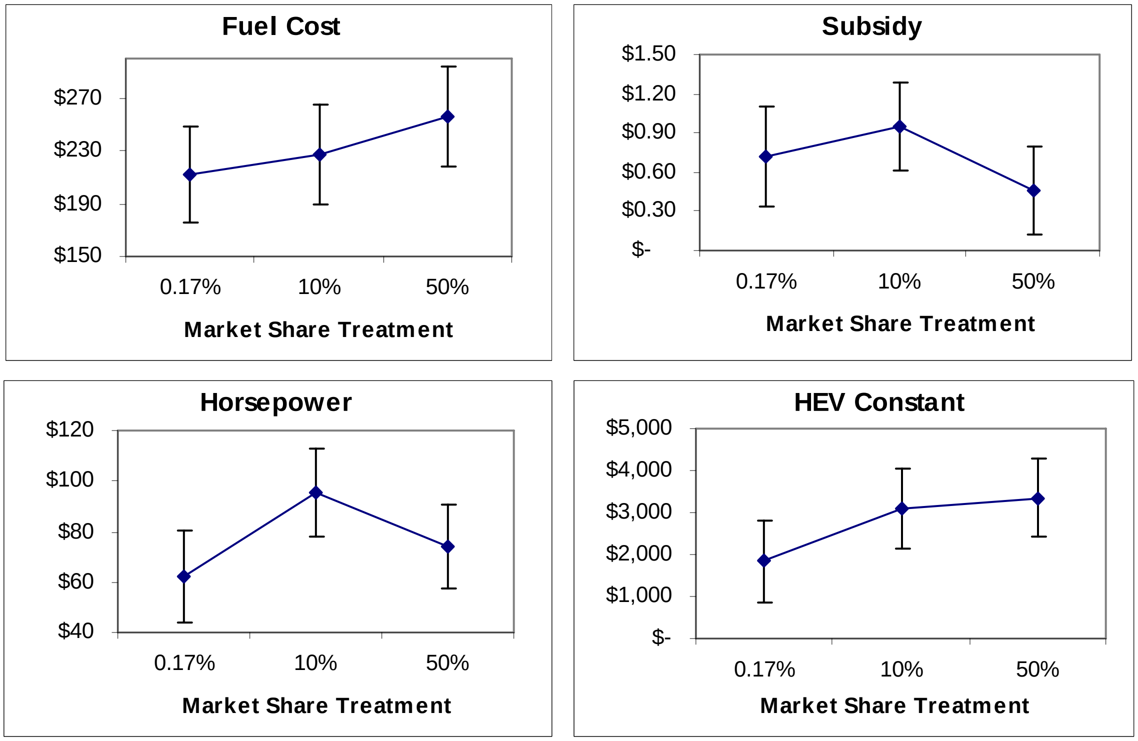
	MS 1 - 3%	MS 2 - 10%	MS 3 - 50%
Attribute	**$ Value**	**$ Value**	**$ Value**
Fuel Cost (per $/week reduced)	$226	$232	$228
Subsidy (per extra dollar)	$0.57	$0.26	$0.22
Power (Per extra unit horsepower)	$115	$83	$66
Hybrid Constant (Premium for HEV)	$3,630	$1,745	$4,168

3.2.4 Comparing Market Share Scenario Groups

The main objective of this study was to investigate how consumer preferences change under different market conditions. In particular, I expected the non-monetary value of HEVs to increase in higher HEV market share scenarios. Figure 25 visually explores this hypothesis, displaying the variation of all four monetized coefficients across the three Canada SP market share treatments (with whiskers representing 95% confidence intervals). In comparing the monetized values, I implicitly assume that the capital cost coefficient is constant across treatments. Each coefficient exhibits some degree of variation, which can stem from two potential drivers: normal modelling error and experimental effect. It is difficult to tease out these drivers, as their influences could offset one another.

For the purposes of this study, I assume that the irregular variation in subsidy and power stem purely from modelling error, as there are no clear trends. For instance, the power attribute is valued at $62 per unit of horsepower at a low market share, $95 at a medium market share, and $74 at a high market share. I have no behavioural explanation for this pattern. On the other hand, the fuel cost attribute and HEV constant appear to follow a consistent trend, becoming more important at higher market shares. For instance, the increasing trend of the HEV constant indicates that consumers are willing to pay an extra $1,851 for hybrids at a low market share, $3,088 at a medium market share, and $3,354 at a high market share. These dynamics in preferences for fuel efficiency and HEVs could be explained as a result of the neighbour effect, where respondents were influenced by the choices of other (hypothetical) consumers. However, only non-monetary attributes are captured in the neighbour effect in CIMS, and thus potential fuel cost preference dynamics are ignored. In this study, the HEV constant was assumed to capture the full neighbour effect, as the only other non-monetary attribute, power, appeared to be static.

Figure 25: Dynamics of Monetized SP Coefficients – 95% Confidence Intervals (Canada)



Under these assumptions, I have integrated all three SP choice models into a single 'dynamic' model. With capital cost, fuel cost, subsidy and power preferences held static across market share conditions, the data from all three treatments was pooled to yield a more statistically significant model. Unique HEV constants were estimated for each market share treatment by adding two ASC interaction terms for MS2 and MS3. The full model is portrayed in Table 15, along with the monetized value of each coefficient, and 95% confidence intervals. Both market share interaction terms are positive, indicating that the value of an HEV increased by 0.1955 ($1,311) and 0.2204 ($1,478) in the 10% and 50% market share scenarios, respectively, relative to the current scenario. In other words, the average consumer would be willing to pay an HEV premium of $1,853 in the MS1 scenario, $3,164 in the MS2 scenario ($1,853 + $1,311), and $3,331 in the MS3 scenario ($1,853 + $1,478).

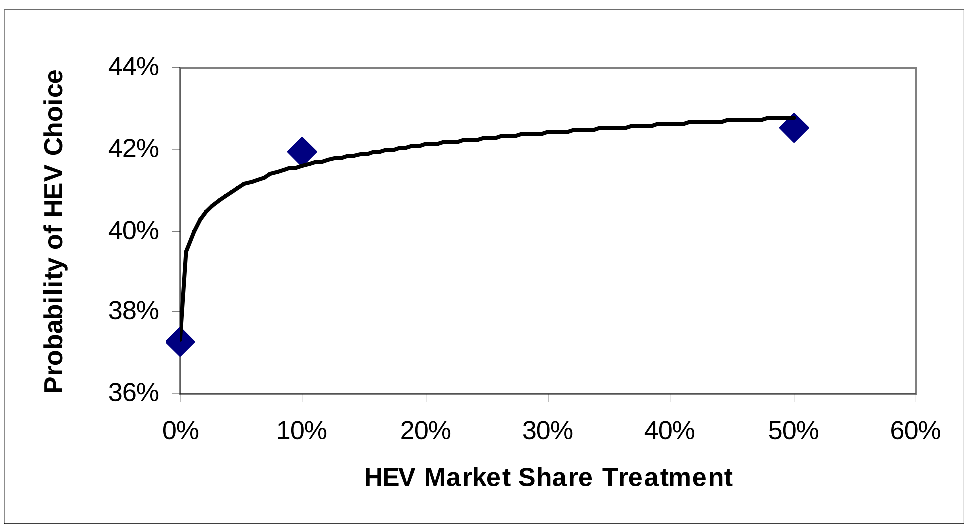
Table 15: 'Dynamic' Canada SP Model – All Treatments Combined

Attribute	Coefficient	t-Value	Monetized	95% Confidence Interval	
Capital Cost	-0.00015	-31.03 (0.00)			
Fuel Cost	-0.03436	-20.86 (0.00)	$230	$209	$252
Subsidy	0.000106	6.95 (0.00)	$0.71	$0.51	$0.91
Power	0.011555	15.14 (0.00)	$77	$67	$88
HEV ASC	0.27641	5.30 (0.00)	$1,853	$1,168	$2,538
Const*MS2	0.19552	3.38 (0.00)	$1,311	$551	$2,070
Const*MS3	0.22038	3.83 (0.00)	$1,478	$721	$2,234
# of Obs	8874				
Chi-Square	1752.52 (0.00)				
LL	-5239.52				
LL (No coeff)	-6150.99				
LL (ASC only)	-6115.78				
LL ratio	0.148				

Notes: p-values in brackets, LL refers to the Log Likelihood of the model, which are also shown for models specified with no coefficients and constants only for comparison.

As expected, this dynamic model yielded higher t-values and chi-square values than the three treatment models on their own (Table 10). Because the number of observations used to estimate the model tripled, the dynamic model had improved explanatory power. However, the 95% confidence interval for each monetized attribute suggests a wide range of potential values, particularly for HEV constants (uncertainty is explored in more detail in Section 3.5). The market share predictions of this model for the three HEV market share scenarios are presented in Figure 26. Again, attribute levels are taken from the 2006 Honda Civic and Civic HEV. A logarithmic trend line is portrayed, which fits much closer than a linear function. This curve indicates that the information acceleration treatment effectively influenced the stated preferences of consumers, mimicking the neighbour effect. In addition, it appears that the strength of neighbour effect diminishes at higher market share levels. Although this curve follows an intuitively pleasing shape, the HEV new vehicle market shares predicted by the SP choice models (37-42%) do not reflect the observed market share in the 2005 Canadian market (0.17%). Part of this overestimation was likely a result of the hypothetical nature of the SP methodology, as consumers tend to indicate much higher preferences for environmental technologies than revealed by actual market data (e.g. Mau, 2005). However, it is also possible that this SP model did not specify other important factors, such as the long waiting lists typically experienced by HEV consumers (often 6 months or longer).

Figure 26: 'Dynamic' Choice Probability Predictions – 2006 Honda Civic Vs. Civic Hybrid



I also compared the California market share treatment groups. The information acceleration treatment was not nearly as effective with the California sample as it was with the Canada sample. As seen in Table 14, the monetized hybrid constants did not follow a sensible pattern across market share groups. The HEV premium was estimated at $3,630 for the current scenario, down to $1,745 for the 10% scenario, and up to $4,168 for the 50% scenario. I suspect that this inconsistency stems from the relatively poor quality of the California sample, as detailed in Section 3.2.1. Over 20% of the California MS1 group spent less than 30 seconds viewing the information acceleration treatment, which could have substantially diminished the influence of the hypothetical neighbour effect. Alternatively, the California treatment may have failed due to respondent resistance to government regulation, as was indicated in the attitude section of the survey.

3.2.5 Demographic Variables

As an added exercise, I experimented with the addition of demographic variables to the choice models, a common practice in choice modelling research. Demographic variables are not typically included in choice models used to inform CIMS, as CIMS is an aggregate model of the entire economy and does not consider the characteristics of individual decision makers. However, demographic analysis can still yield interesting, relevant findings for policymakers, such as revealing the diversity of preferences among consumer segments. In addition, the inclusion of demographics can indicate just how important these variables are in the choices under examination.

I tested several demographic combinations, interacting income, education and family size variables with the capital cost coefficient and HEV constant. The best of these models is summarized in Table 16, alongside the ‘dynamic’ SP model as a base for comparison. Three demographic interaction variables were specified: capital cost divided by the log of household income, the hybrid constant multiplied by the log of household income, and the hybrid constant multiplied by a dummy indicating the presence of children (1 = one or more children, 0 =none). The significance of these variables indicate three tendencies: 1) capital cost is a less influential attribute for respondents with higher income levels; 2) respondents with higher income are less likely to choose HEVs; and 3) respondents with children are more likely to choose HEVs. The demographic model is a significant improvement (by chi-square test) over the base model. However, the demographic variables are excluded from further analysis because they are not useful for informing CIMS behavioural parameters.

Table 16: Best Demographic Model Compared with Base Model

	Base Model		W/Demographics	
Attribute	**Coeff**	**t-Value**	**Coeff**	**t-Value**
Capital Cost	-0.00015	-31.03 (0.00)		
CC/L(Inc)			-0.00072	-30.72 (0.00)
Fuel Cost	-0.03436	-20.86 (0.00)	-0.03382	-20.35 (0.00)
Subsidy	0.000106	6.95 (0.00)	0.000105	6.78 (0.00)
Power	0.011555	15.14 (0.00)	0.01173	15.23 (0.00)
HEV ASC	0.27641	5.30 (0.00)	1.34405	2.67 (0.01)
ASC*MS2	0.19552	3.38 (0.00)	0.17372	2.99 (0.00)
ASC*MS3	0.22038	3.83 (0.00)	0.22185	3.82 (0.00)
ASC*L(INC)			-0.23275	-2.21 (0.03)
ASC*KIDS			0.16848	3.48 (0.00)
# of Obs	8874		8766	
LL	-5239.52		-5174.10	
LL (No Coeff)	-6150.99		-6076.13	
LL (ASC Only)	-6115.78		-6039.94	
LL Ratio	0.148		0.148	

Notes: p-values in brackets, LL refers to the Log Likelihood of the model, which are also shown for models specified with no coefficients and constants only for comparison.

3.3 Revealed Preference (RP) Models

The online survey also collected RP data, primarily to facilitate the estimation of joint models from SP and RP data. RP data was intended for use as a grounding force to counter the potentially unreliable nature of SP data. This section presents choice models estimated from RP data only. Two major issues in RP modelling should first be explained: multicollinearity, and choice-based weighting.

First, one of the largest drawbacks of RP choice modelling is its susceptibility to multicollinearity. This phenomenon occurs when explanatory variables (attributes) are strongly correlated, leading to insignificant and/or counterintuitive coefficient estimates. As discussed in Section 2.1.4, vehicle attributes tend to be highly correlated. Table 17 confirms this tendency for the RP data collected in this study with a correlation matrix of the key attributes. Notice that many correlation values are between 0.3 and 0.7, which are substantial. These high correlations are generally intuitive, such as the tendency for more powerful vehicles to be more costly and less fuel efficient.

Table 17: Correlation Matrix of RP Attributes

	HEV Constant	Capital Cost	Fuel Efficiency	Fuel Price	Fuel Cost	Horse Power
HEV Constant	1					
Capital Cost	-0.087	1				
Fuel Efficiency	-0.586	0.317	1			
Fuel Price	0	0.006	0	1		
Fuel Cost	-0.222	0.144	0.385	0.179	1	
Horsepower	-0.394	0.625	0.715	-0.011	0.287	1

A second issue of this RP modelling process is weighting. As detailed in Section 2.3.1 (sampling), a choice-based sampling technique was required to recruit a significant sample of HEV owners in Canada and California. Thus, HEV owners were overrepresented in the sample, which had to be corrected by weighting the choice data to reflect the true choice market shares portrayed in Table 18. For example, the Canada RP sample included 9% HEV owners, but actual HEV new market share was 0.17% in 2005.[7] The choice modelling software corrected for this by multiplying the likelihood values calculated for HEV choice observations by a weight of 0.019, greatly reducing the influence of these choices on model estimation. This weighting procedure was completed for all 12 vehicle classes.

Table 18: Weighting Scheme Correcting Choice Based Sampling in RP Models

		Corrected New Vehicle Market Share %	
Vehicle Class	**Engine Type**	**Canada**	**California**
Sub-Compact Car	Gas	9.31%	6.85%
Compact Car	Gas	46.17%	37.69%
Midsized Car	Gas	7.29%	11.60%
Large Car	Gas	1.21%	3.16%
Small SUV	Gas	4.05%	3.69%
Midsized SUV	Gas	11.14%	15.82%
Large SUV	Gas	0.81%	4.48%
Minivan	Gas	15.19%	5.27%
Large Van	Gas	0.20%	-
Small Pickup Truck	Gas	1.21%	4.48%
Large Pickup Truck	Gas	3.24%	3.95%
Hybrid Electric	Hybrid	0.17%	3.00%
Total		**100.00%**	**100.00%**

[7] All survey respondents purchased new vehicles between 2002 and 2006, so it was not entirely accurate to apply the 2005 HEV weighting to all respondents. The weighting procedure I used in this study only allowed me to weight by vehicle choice, not by vehicle year. Thus, I chose 2005 as a base year because the best market data was available for this year, and this year also coincides with the first simulation period portrayed in CIMS. I feel this was a reasonable simplification.

With attribute correlation and choice weighting in mind, RP-based MNL models were estimated for Canada and California (Table 19) according to the utility function in Equation 13. Both models have significant chi-square values, and most coefficient estimates are significant at a 99% confidence level. As an exception, the Canada horsepower coefficient has a relatively low t-value and counterintuitive sign (indicating that consumers prefer less horsepower). This coefficient was expected to be problematic, as horsepower exhibited a high degree of correlation with other attributes. The log-likelihood ratios (pseudo R^2) of both RP models are significantly higher than the SP models (such as Table 10), indicating that, statistically, the RP model has more explanatory power.

Table 19: RP Choice Models Estimates – Excluding Vehicle Class

	Canada - RP		California - RP	
Attribute	**Coefficient**	**t-Value**	**Coefficient**	**t-Value**
Capital Cost	-0.0000297	-5.30 (0.00)	-0.000140	-13.38 (0.00)
Fuel Cost	-0.0639	-7.02 (0.00)	-0.0669	-7.20 (0.00)
Horsepower	-0.00263	-1.44 (0.15)	0.0188	11.44 (0.00)
HEV ASC	-7.861	-5.42 (0.00)	-1.840	-4.31 (0.00)
# of Choices	542		414	
LL	-983.69		-683.99	
LL (No coefficients)	-1344.33		-992.73	
LL ratio	0.27		0.31	
Monetized				
Fuel Cost	$2,152		$478	
Horsepower	- $89		$134	
Hybrid Constant	- $264,680		- $13,143	

Notes: p-values in brackets, LL refers to the Log Likelihood of the model, which are also shown for models specified with no coefficients for comparison.

The monetized coefficients in Table 19 are vastly different from SP estimates. For example, the Canada monetized fuel cost coefficient of $2,152 (the amount a consumer is willing to pay extra in purchase price to reduce weekly fuel costs by $1) is roughly 10 times the magnitude of corresponding coefficients in the SP models. The Canada HEV constant is also extremely high, indicating that consumers would require a savings of $264,680 to equate an HEV with a conventional vehicle. These estimates are not realistic from an intuitive standpoint, nor are they comparable with previous studies.

A more advanced RP model is presented in Table 20, which estimates constants for each vehicle class. This addition greatly improved the explanatory power of both RP models, as indicated by higher log likelihood values and ratios. The subcompact vehicle class constant was assigned an arbitrary value of zero, and was thus the base of comparison for all other class constants. For example, the Canada compact car constant of 0.8900 is positive relative to the subcompact car (zero), and thus more desirable. Similarly, the HEV constant is also interpreted relative to subcompact cars, where the HEV is the least desirable class in the Canada sample, and roughly middle of the pack for the California sample.

To put it bluntly, I have little confidence in these models. The attribute data has enormous collinearity problems, and many of the monetized coefficients are nonsensical, particularly in the Canada models. I would not recommend using this RP methodology to inform CIMS, or to perform any significant policy analysis. Interestingly, the California models were less affected by collinearity problems, as monetized fuel cost and horsepower estimates were substantially closer to SP model estimates. I cannot explain this difference, as both Canada and California models drew attribute data from the same vehicle database.

Table 20: RP Choice Models Estimates – Including Vehicle Class

	Canada - RP		California - RP	
Attribute	**Coefficient**	**t-Value**	**Coefficient**	**t-Value**
Capital Cost	-0.0000443	-6.97 (0.00)	-0.000159	-13.49 (0.00)
Fuel Cost	-0.0280	-3.31 (0.00)	-0.0325	-4.04 (0.00)
Horse-power	0.00015	0.08 (0.94)	0.0205	10.70 (0.00)
Constant	**Coefficient**	**t-Value**	**Coefficient**	**t-Value**
Compact Car	0.8900	5.23 (0.00)	1.0749	4.44 (0.00)
Midsized Car	-0.2550	-1.18 (0.24)	0.0703	0.26 (0.79)
Large Car	-1.6381	-3.87 (0.00)	-1.0680	-2.78 (0.01)
Small SUV	-1.4028	-5.03 (0.00)	-1.2479	-3.70 (0.00)
Midsized SUV	0.3549	1.63 (0.10)	0.5608	1.83 (0.07)
Large SUV	-1.2569	-2.52 (0.01)	0.5872	1.52 (0.13)
Minivan	0.3205	1.59 (0.11)	-0.6702	-2.13 (0.03)
Large Van	-3.4924	-3.55 (0.00)	-	-
Small Pickup	-2.6000	-5.94 (0.00)	-1.9212	-5.65 (0.00)
Large Pickup	-0.6445	-1.87 (0.06)	-1.4349	-3.88 (0.00)
Hybrid	-5.3986	-4.86 (0.00)	-1.0142	-2.35 (0.02)
# of Choices	542		414	
LL	-807.28		-549.69	
LL (No coeff)	-1344.33		-992.73	
LL ratio	0.40		0.45	
Monetized Attributes				
Fuel Cost	$632		$204	
Horsepower	$3		$129	
Hybrid Constant	- $121,865		- $6,379	

Notes: p-values in brackets, LL refers to the Log Likelihood of the model, which are also shown for models specified without coefficients for comparison.

Despite the many problems of these RP models, this exercise has yielded three important observations. First, the addition of class constants substantially improved the power of both the Canada and California models, and brought coefficient estimates closer to the more intuitively reasonable values estimated in the SP models. Thus, class specification appears to be a valuable addition to vehicle choice models. Secondly, although I have little confidence in the absolute values of the HEV constants, the proportional difference between Canada and California could be used to estimate the declining intangible cost function for CIMS. Finally, this RP technique illustrated the value that a jointly estimated choice model could add by eliminating collinearity issues while including the seemingly important vehicle class specification. A joint estimation procedure is described next.

3.4 Joint SP-RP Choice Models

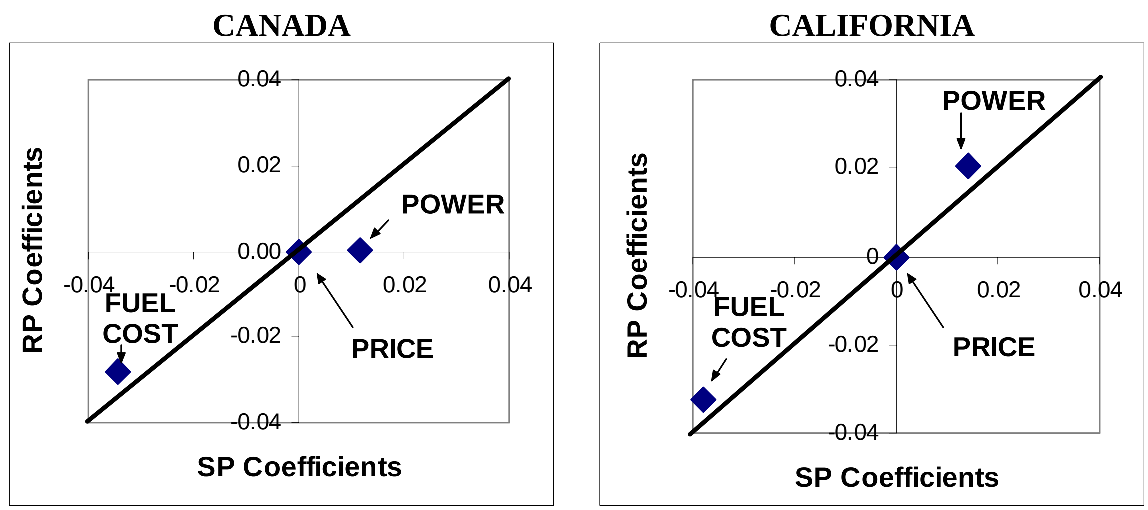
I derived joint SP-RP choice models using the 'sequential' method described in Section 2.1.4. The 'pooling' of attribute data from RP and SP sources was not appropriate given the observed problems of the RP data and models. Instead, the 'sequential' approach estimates attribute coefficients from the SP data only, then calibrates RP constants to reflect the true market shares in the RP data.

The first step of the 'sequential' approach was to estimate the scale factor, λ, to account for scaling differences between the RP and SP models. Using the 'artificial' nested logit technique described in Section 2.1.3 and 2.1.4, this scale factor was calculated to be 1.0 for both the Canada and California samples. This finding means that RP and SP models in each sample exhibited similar error variance, and thus parameters did not need to be adjusted when forming a composite utility function. Hensher et al. (2005) state that it is common to find a scale factor of 1.0 for SP and RP models that have been estimated from the same sample.[8]

[8] The samples used for the RP and SP models are not exactly the 'same', as the HEV owners included in the RP model were excluded from the SP models.

This scale factor estimate was confirmed using a visual test described by Louviere et al. (2000). Each coefficient that is common to both models (capital cost, fuel cost and power) was plotted with the SP estimate on one axis, and the RP estimate on the other (Figure 27). If the scale of the RP and SP models are equal (1.0), then the coefficient plots should follow the shown trend line with a slope of one and a zero intercept. Both samples appear to be very close to this ideal, except for the Canada power coefficient, which has already been identified as suffering from collinearity problems. Otherwise, this visual depiction confirms the calculation of equal scale values.

Figure 27: Visual Test for Coefficient Equality across RP and SP Choice Models



The next step of the 'sequential' estimation process was to extract the attribute coefficients from 'best' SP models, which were judged to be the integrated dynamic Canada (Table 15) and California models.[9] These coefficients were then implanted as fixed values into the class-specific RP models estimated in Table 20. This step eliminated

[9] The 'dynamic' SP California model, which combined all three treatment groups into a single model, was not portrayed in this section, as it did not yield additional insights.

the problematic RP attribute coefficients. Finally, this composite choice model was calibrated to fit the weighted RP data, as the vehicle class constants had to be re-estimated to accommodate the new SP coefficients. The final joint models are portrayed in Table 21, and are highly significant. Subsidy coefficients were not included in this model, because subsidy levels were not available in the RP data.[10] The RP constants are different from the RP-only models as a result of the recalibration procedure. These models represent the best available information from the RP and SP models.

From a purely statistical perspective, the joint models have less explanatory power than their RP-only counterparts do. The coefficients estimated in the RP models maximized the log likelihood of the overall model. Thus, to fix the attribute coefficients at any value other than their maximum likelihood estimate (MLE) inevitably results in suboptimal log likelihood values and ratios. However, given what is known about the strengths and weaknesses of SP and RP data sets, I place a much higher degree of confidence in the explanatory power of the joint models.

The monetized attribute values presented in Table 21 are far more realistic than those calculated from the RP-only models. The fuel cost and horsepower coefficients are nearly identical for the Canada and California models. The substantial difference in hybrid constants confirms the presence of the neighbour effect, decreasing from roughly $32,000 to $7,000 with an increase in HEV penetration from 0.17% to 3.0%. Although the $32,000 HEV intangible cost for Canadians may still seem high (although far more realistic than the RP estimate of $120,000), consider that this estimate is for the *average*

[10] The subsidy coefficient was estimated in the SP models that informed the joint models, as the subsidy was an important part of the SP treatment, and improved the explanatory power of SP models. However, the subsidy attribute could not be included in the joint models.

consumer. Many Canadians did not know about HEVs when they purchased their vehicles, or didn't have access to dealers that sold them, so intangible costs were nearly infinite for this segment. This raised the average intangible cost to a seemingly high value, but this is logical given the very low HEV penetration rate of 0.17%.

Table 21: "Joint" SP-RP Models – Canada and California

	Canada - Joint		California - Joint	
SP Attributes	**Coefficient**	**t-Value**	**Coefficient**	**t-Value**
Capital Cost	-0.000149	**Fixed**	-0.000165	**Fixed**
Fuel Cost	-0.0344	**Fixed**	-0.0378	**Fixed**
Horse-power	0.0116	**Fixed**	0.0143	**Fixed**
RP Calibrated Constants	**Coefficient**	**t-Value**	**Coefficient**	**t-Value**
Compact Car	0.8637	3.85 (0.00)	1.0006	3.87 (0.00)
Midsized Car	-0.3392	-1.29 (0.20)	0.2882	1.04 (0.30)
Large Car	-1.7788	-3.87 (0.00)	-0.6985	-1.84 (0.07)
Small SUV	-1.4380	-4.66 (0.00)	-1.3434	-3.91 (0.00)
Midsized SUV	0.3109	1.12 (0.26)	0.9638	3.27 (0.01)
Large SUV	-0.3919	-0.70 (0.48)	1.5357	4.86 (0.00)
Minivan	0.3808	1.67 (0.09)	-0.3568	-1.15 (0.25)
Large Van	-4.0560	-4.22 (0.00)	-	-
Small Pickup	-3.2862	-7.17 (0.00)	-1.7139	-5.23 (0.00)
Large Pickup	-0.8265	-2.53 (0.01)	-0.6384	-1.84 (0.07)
Hybrid	-4.7772	-4.47 (0.00)	-1.2231	-3.28 (0.01)
# of Choices	541		414	
LL	-913.17		-561.61	
LL (No coeff)	-1344.33		-992.73	
LL Ratio	0.32		0.43	
Monetized Attributes				
Fuel Cost	$230		$229	
Horsepower	$78		$87	
Hybrid Constant	- $32,061		- $7,393	

Notes: p-values in brackets, LL refers to the Log Likelihood of the model, which are also shown for models specified with no coefficients for comparison

Finally, Table 22 presents the market shares predicted by the joint choice models. Each vehicle class was represented with average attribute levels for that class in the RP data. The attributes of the 2006 Civic HEV where once again used for the HEV class. These predicted values can be compared with the observed market share values in Table 18 of the previous section. The predicted market shares are considerably lower for HEVs than currently observed in both Canada (0.06% vs. 0.17%) and California (0.65% vs. 3.0%). These models were not expected to yield perfectly accurate market share forecasts, as the entire passenger vehicle sector is represented with only 12 technologies, with only one type of HEV. However, the differences between market shares predicted by each model are proportionally the same between California and Canada, indicating that the models realistically accounted for HEV preference differences between the regions.

Table 22: Vehicle Class Market Shares Predicted by 'Joint' Choice Model

	Assigned Attribute Levels			**Predicted Market Share %**	
Vehicle Class	**Purchase Price**	**Weekly Fuel Cost**	**Horse-Power**	**Canada**	**California**
Sub-Compact	$24,247	$23	133	13.89%	8.07%
Compact Car	$22,937	$21	137	44.81%	31.13%
Midsized Car	$28,656	$26	199	9.90%	13.04%
Large Car	$29,500	$29	235	2.85%	8.43%
Small SUV	$30,845	$28	155	1.35%	2.11%
Midsized SUV	$32,902	$34	216	9.45%	14.99%
Large SUV	$56,500	$41	291	0.25%	8.50%
Minivan	$29,135	$30	190	15.17%	3.94%
Large Van	$24,000	$42	285	0.76%	-
Small Pickup	$28,833	$34	196	0.38%	3.42%
Large Pickup	$41,481	$38	255	1.14%	5.71%
Hybrid Electric	$28,000	$13	93	**0.06%**	**0.65%**
Total				**100.00%**	**100.00%**

In summary, the joint models estimated in this section appear to have successfully combined the respective strengths of SP and RP modelling approaches while mitigating weaknesses. First, the hypothetical and unreliable nature of the SP models was grounded in the market reality of the RP data. Second, the problematic RP attribute coefficients were replaced by SP coefficients estimated in an experiment that carefully elicited consumer trade-offs. Thus, the joint models are an appropriate source of vehicle choice coefficients to be integrated into the CIMS model. The next section makes one final comparison of the estimation procedures outlined in this chapter through uncertainty analysis.

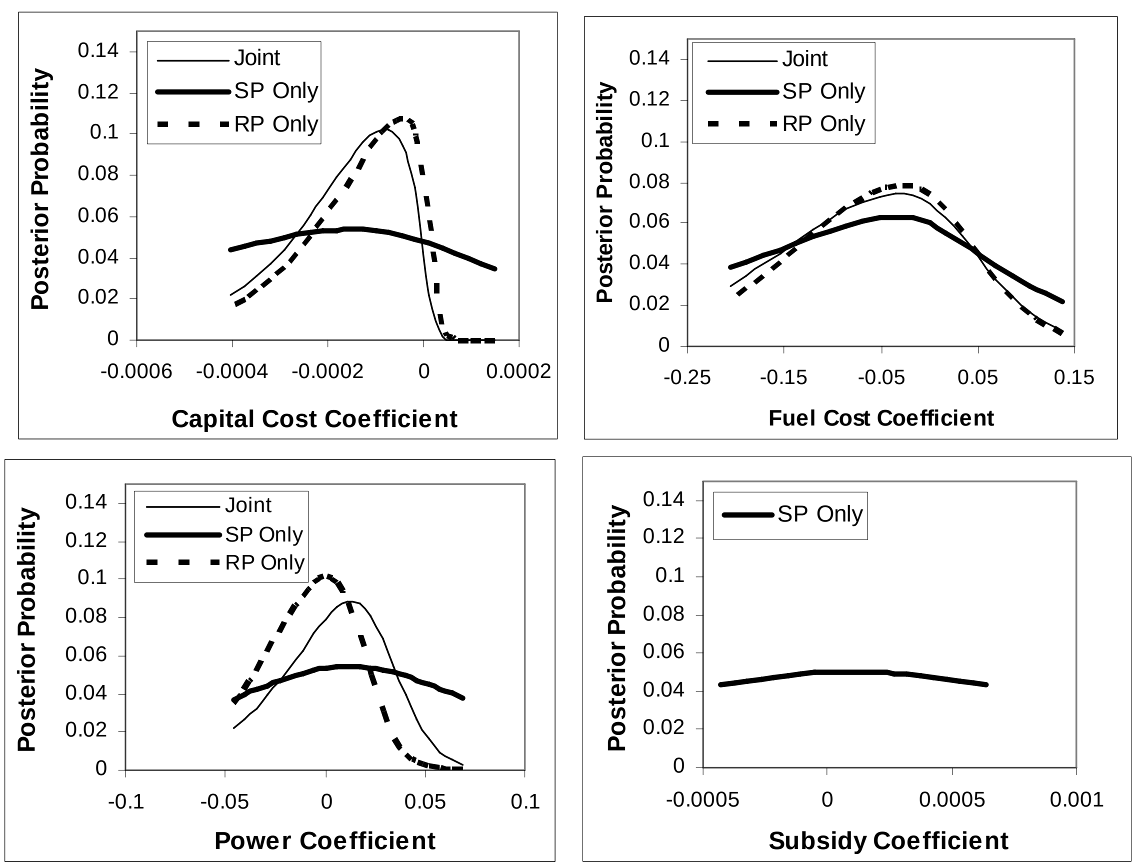
3.5 Uncertainty in Choice Models

So far, in the description and comparison of SP, RP and joint modelling approaches, little attention has been devoted to the certainty of model estimates. As described in Section 2.4, not only does uncertainty analysis help to communicate the degree of confidence one should have in model estimates, but it also helps to compare the relative certainty of different modelling approaches. In this section, I present an uncertainty analysis of both the coefficient estimates and market share forecasts of selected SP, RP and joint choice models using the Bayesian and Monte Carlo simulation techniques introduced in Section 2.4.

3.5.1 Coefficient Estimates

The uncertainty of each model coefficient was assessed as a posterior probability distribution, using Equation 14. These probabilities were ‘conditional’, that is, calculations were made while holding all other coefficients constant. The prior distributions were uniform, which assumes that I had no prior information about the coefficient estimates, and assured that the estimated posterior probabilities were informed only by the data collected in this study. The range for each coefficient distribution was subjectively determined. I chose to adjust the range until the distribution tails were in a 1-2% probability range where possible. For the purposes of comparison, I used the same distribution range for a given attribute in the selected SP, RP and joint models. The resulting posterior probability distributions are portrayed for each attribute coefficient in Figure 28 (subsidy was only included in the SP model). Only the Canada models are discussed in this section, but the California coefficients exhibited nearly identical trends.

Figure 28: Comparing Coefficient Probability Functions from Different Models (Canada)

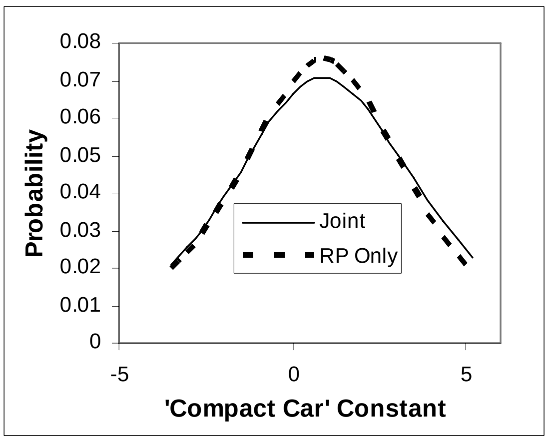


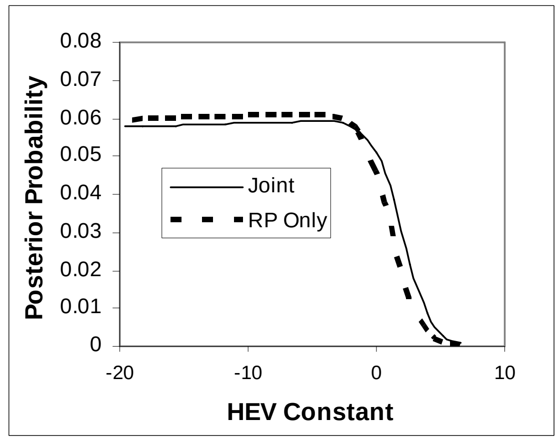
Each distribution function in Figure 28 follows a typical bell-shaped curve, although some are slightly skewed. Generally speaking, the coefficient estimates appear to be quite diffuse, with a wide range of values that are almost as likely as the maximum likelihood estimate (MLE) provided by the choice models. The capital cost coefficient was specified at a ranged of +/- 200%, while the other three coefficients were varied +/- 500%. Similar distribution ranges of 500-1000% were required for SP coefficients in previous studies using this Bayesian uncertainty methodology (Eyzaguirre, 2004; Mau, 2005). The fuel cost, power and subsidy coefficients are particularly diffuse, as values of either sign are almost equally probable in all three models.

Comparing the three modelling approaches, the coefficients estimated by the SP method are the most diffuse, and thus the least certain. The RP and joint coefficients are similarly distributed, but the RP probability distributions are slightly more distinct than the joint coefficients. As discussed in Section 3.4, the RP model is inevitably more certain than the joint model when using only statistical criteria. However, this analysis indicates that the RP coefficients are only slightly more certain than the joint model coefficients, and both are substantially more certain than the SP coefficients.

Two class constant distributions are displayed in Figure 29, yielding similar trends as the other coefficients. These constants were only specified in the RP and joint models, and both distributions are diffuse. The 'compact car' estimate is almost as likely to be positive as it is negative. The HEV constant is also diffuse, but exhibits an interesting trend where probability is relatively uniform for extremely low values, but drops sharply for positive values. I suspect that this behaviour is due to the very low RP market share of HEVs in the choice model. The HEV choice represents such a small proportion of overall vehicle choices that an unrealistically low HEV constant would not significantly handicap the model's predictive capabilities. On the other hand, an unrealistically high HEV constant would be more problematic, causing the model to predict an incorrectly high penetration of HEVs.

Figure 29: Comparing *ASC* Probability Functions from Different Models (Canada)





It is difficult to interpret the observed differences among the three modelling approaches. It is tempting to conclude that the joint model is simply more realistic and reliable than the SP model, which may be the case. However, these distribution patterns were also likely influenced by the different choice structures of the SP and joint model. The joint model was based on RP data, which specified 12 choices per choice set, while the SP data only specified two choices per set. With more choices, the RP data was more susceptible to making a wrong prediction when coefficient estimates were varied from their MLE. Thus, I would expect posterior probability distributions for these coefficients to follow a more distinct shape than the SP coefficients estimated from binary choice sets. Given this tendency, it may be inappropriate to compare the distributions in Figure 28 at face value only.

In summary, this Bayesian uncertainty analysis indicates that there is substantial uncertainty in the coefficients estimated by all three modelling approaches. The RP and joint models produced relatively less uncertain coefficient distributions than the SP models, which could justify the inclusion of RP data in the estimation of behavioural parameters in CIMS. However, it is clear that the high uncertainty in these coefficients must be translated into the parameters and simulation forecasts that they are used to derive.

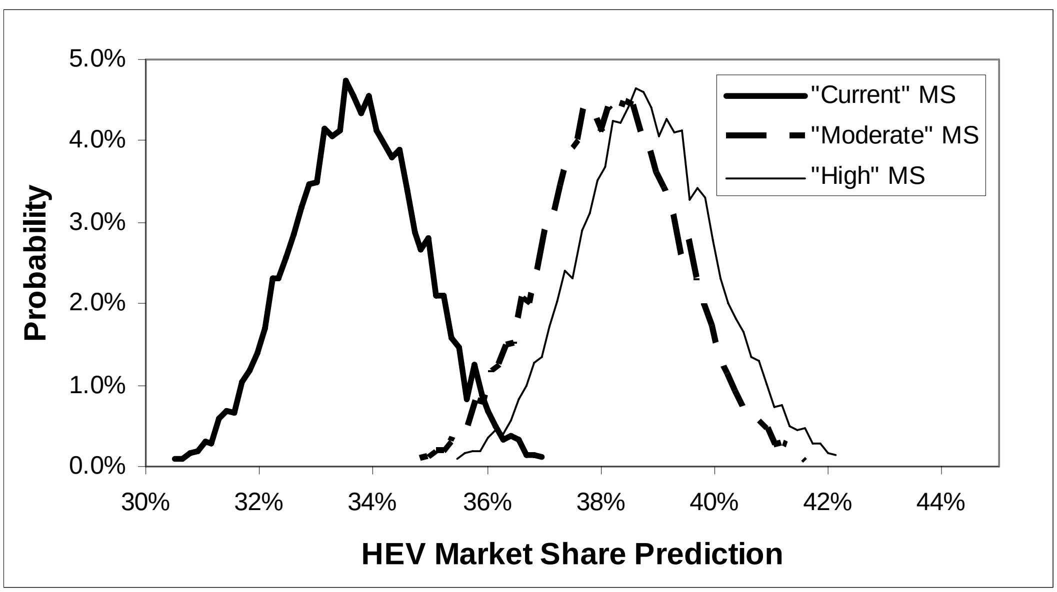
3.5.2 Market Share Forecasts

An uncertainty analysis was also conducted on the market share values predicted by the choice models, using a Monte Carlo simulation technique. Monte Carlo simulation was introduced in Section 2.4.2 as a useful method of assessing the uncertainty in output values that are calculated from uncertain inputs. This technique is appropriate here because market share predictions are calculated from uncertain choice model coefficients.

In Monte Carlo simulation, a probability distribution must be specified for each input parameter. In this study, each choice model coefficient was assigned a normal distribution based on its MLE (mean) and standard error (standard deviation). Note that this constitutes a classical statistical approach, as opposed to the Bayesian approach followed in the previous section. A classical approach was chosen as it provided for a more objective and consistent arrangement of ranges among coefficients (based on standard error). In addition, this approach allowed the specification of correlations among coefficients, which adds to the realism of the random draws. Correlations were calculated from the covariance matrices produced as outputs of the choice models estimated in LIMDEP. 10,000 random draws were conducted for each market share prediction.

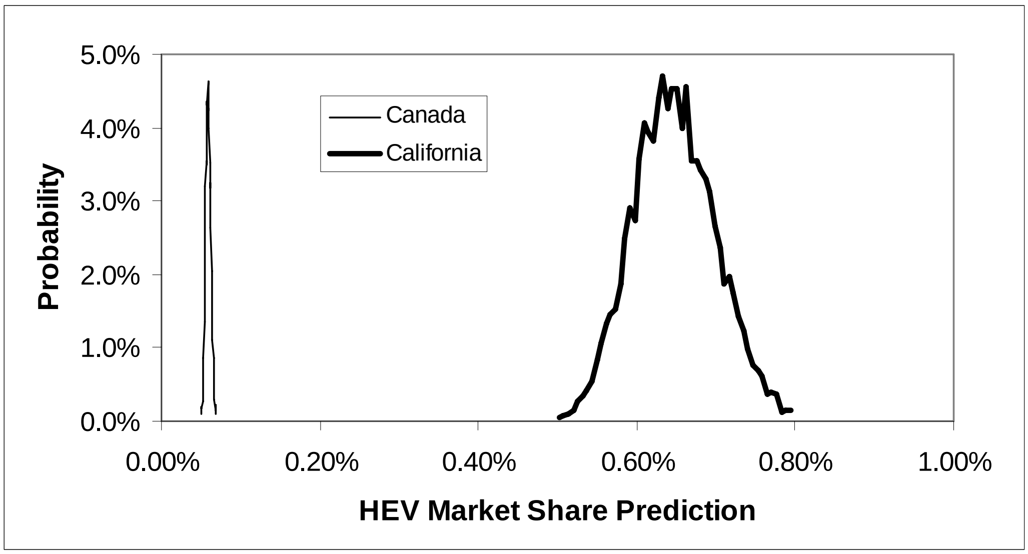
Figure 30 plots the frequency distributions of the HEV market share predicted by the ‘dynamic’ SP model for each market share scenario. Each distribution ranges about +/- 3% of the MLE, which is distinct. The market share predicted for the ‘current’ scenario is significantly lower than the ‘moderate’ or ‘high’ scenarios. However, the ‘moderate’ and ‘high’ scenario predictions have substantial overlap. Thus, I cannot conclude that the SP experiment yielded ‘moderate’ and ‘high’ HEV penetration models that are significantly different from one another.

Figure 30: Monte Carlo Simulation - SP Market Share Predictions (Canada)



The market share distributions of the joint models estimated in Section 3.4 are displayed in Figure 31. Both the Canada and California models yield distinct forecasts. In addition, there is no overlap between the models, providing confidence that the models are significantly different. As expected, the Canada model predicts a market share much lower than California (0.06% versus 0.60%), which is proportionally similar to the actual market shares of the two regions (0.17% versus 3.0%). It is reasonable to conclude that the Canada and California samples have significantly different preferences for HEVs.

Figure 31: Monte Carlo Simulation - Joint Market Share Predictions (Canada and California)



In summary, despite the high degree of uncertainty in the choice model coefficients, the Monte Carlo procedure used in this section indicates that the HEV market shares estimated in the SP and joint models are reasonably certain. However, it is still very important to communicate the existing uncertainty to users of the models. For these reasons, these uncertainty were carried over into parameters derived for CIMS.

CHAPTER 4: IMPROVING THE CIMS MODEL

The previous chapter described the estimation of several discrete choice models from stated preference (SP) and revealed preference (RP) data collected with an online survey. A joint modelling technique achieved a balance of qualitatively and quantitatively reliable coefficient estimates relative to techniques using only SP or RP data. This chapter outlines the final stage of this study, which used the best choice models from Chapter 3 to inform CIMS, the hybrid energy-economy policy model. This chapter is divided into four sections. The first section details the derivation of behavioural parameters (r, i and v) for CIMS from choice model coefficients. Coefficients were primarily extracted from the Canada and California joint models, while the Canada SP model was used to approximate intangible cost dynamics for longer-term scenarios. The second section of this chapter summarizes how the inclusion of these behaviourally realistic parameters alters CIMS forecasts. The third section presents a sensitivity analysis characterizing how uncertainty in behavioural parameter estimates influences simulation outputs. The final section presented simulations of four policies using the improved CIMS model: a carbon tax, subsidy scheme, feebate program, and vehicle emissions standard (VES).

4.1 Calculating Behavioural Parameters

4.1.1 Discount Rate (*r*)

The discount rate was calculated using Equation 15 (restating Equation 8):

$$r = \frac{\beta_{CC}}{\beta_{OC}} \times (1-(1+r)^{-n}) \qquad \text{Equation 15}$$

Where β_{CC} is the capital cost coefficient; β_{OC} is the coefficient for annual operating costs (fuel costs), and *n* is the technology lifespan. I used Excel's Solver to calculate *r* from the capital and fuel cost parameters from the joint models.[11] The Canada and California joint models yielded nearly identical *r* estimates of 21.6% and 21.8%, respectively. Previous SP choice studies estimated similar values of 22.6% (Horne et al., 2005) and 21.8% (Mau, 2005). The current discount rate used in the passenger vehicle node of CIMS is 30%, which underestimates the weight that consumers place on longer term values (fuel and maintenance costs) relative to shorter term values (capital cost).[12] In other words, this study indicates that consumers are less short sighted when making vehicle purchase decisions than is currently assumed in CIMS.

4.1.2 Intangible Costs Dynamics (*i*, *A*, and *k*)

The intangible (non-monetary) costs of hybrid-electric vehicles (HEVs) were also estimated from the empirical choice models of Chapter 3. I followed Equation 16 (restating Equation 9):

$$i_j = \sum^{N} \left(\frac{\beta_n}{\beta_{CC}} \times X_n \right) \qquad \text{Equation 16}$$

Where the perceived intangible cost, i_j is the sum of monetized intangible coefficients (β_n divided by β_{CC}) multiplied by the value of intangible attributes, X_n. In Section 2.1.1 I

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[11] The technological lifespan, *n*, was assumed to be 16 years, as is specified for HEVs in CIMS.

[12] CIMS actually specifies a discount rate of 8% for an assumed lifespan of 4 years, which is equivalent to a discount rate of 30% for a lifespan of 16 years.

explained that for the purposes of this study, the passenger vehicle node in CIMS has been simplified to include only six gasoline vehicle technologies, with car and truck versions of high-efficiency, low-efficiency and hybrid-electric technologies. Because intangible cost is a *relative* value, it must be calculated relative to a competing technology. I used the high-efficiency vehicle technology in CIMS as the reference, as up to this point the Honda Civic has been used as a baseline for comparison with the HEV. The attributes of the Civic match closest with the high-efficiency vehicle in CIMS (as opposed to the low-efficiency vehicle). I continued to use the attributes of the Civic and Civic Hybrid for the calculation of intangible costs.

Because my objective was to estimate preference dynamics, I estimated intangible costs from choice models representing four HEV market share scenarios. The two lower market share estimates were derived from the Canada (0.17%) and California (3.0%) joint models. The two higher market share estimates were derived from the 'dynamic' Canada SP models (10% and 50%) because RP data was not available for higher HEV penetration scenarios. I detail the HEV intangible cost calculation for the lowest market share scenario in Table 23 for illustration. The total intangible cost difference between the 2006 Honda Civic and its HEV counterpart was $34,662, mostly captured by the *ASC* (92%).[13] The intangible cost of the high-efficiency conventional gasoline vehicle specified in CIMS is $6555.[14] Because I framed the HEV intangible cost relative to this high-efficiency vehicle, the HEV intangible cost entered into CIMS was added to this

[13] This value of $34,662 may appear to be extremely high, but as noted in Section 3.4, this value represents the intangible costs experienced by the *average* consumer. In the 2005 Canadian market, many new vehicle consumers did not know about HEVs, or did not have access to HEV dealers, resulting in nearly infinite costs for some consumers. Thus, the average intangible cost values is very high, which causes CIMS to predict a realistically low 2005 HEV new market share.

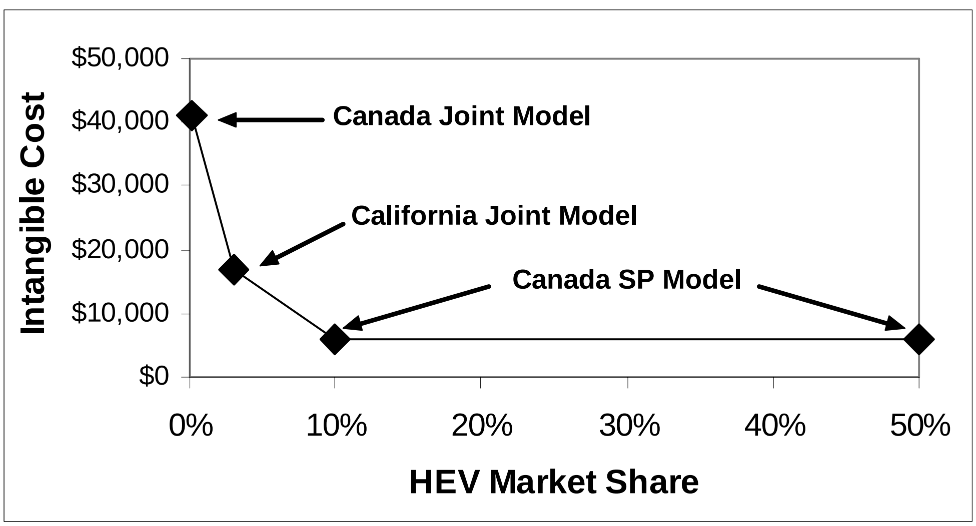
[14] The $6555 intangible cost value currently used high-efficiency vehicles in CIMS was originally extracted from the National Energy Modelling System (NEMS) in the US, and has been calibrated over time.

value ($34,662 + $6555 = $41,217). This procedure was also conducted with the California joint model coefficients, as well as the Canada SP models. Figure 32 plots the resulting data points. This same procedure was also conducted for truck technologies in CIMS.

Table 23: Calculation of HEV Intangible Cost (Car) – 0.17% HEV Market Share

Cost Component	Choice Coefficient	Monetized	Attribute Difference	Intangible Cost
Power (HP)	0.01155	$77.47 per HP	34 HP	$2,634
Other (*ASC*)	-4.777	$32,028	1	+ $32,028
Total				**$34,662**
CIMS High-Eff Vehicle				+ $6,555
Total for CIMS				**$41,217**

Figure 32: Intangible Cost Estimates in Different HEV Market Share Scenarios



Next, I fit the intangible cost function to these four market share estimates using Equation 17 (restating Equation 2):

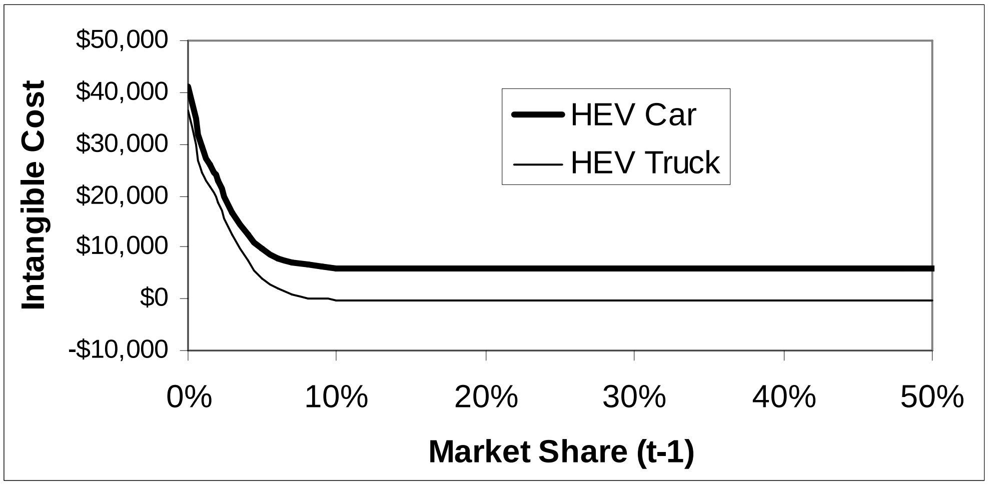
$$i(t) = \frac{i(0)}{1 + Ae^{k^{*}MS_{t-1}}} \qquad \text{Equation 17}$$

Where $i(t)$ 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 time $t-1$, and the A and k parameters are adjusted to fit the curve to the data points. I estimated A and k parameters for both the car and truck HEV (Table 24) using Excel's Solver, to minimize the difference between the curve and the four points. The curve fit best when I divided the intangible costs into fixed and variable components. The resulting declining intangible cost function is plotted in Figure 33, which follows the same shape of the intangible costs in Figure 32. The truck function is about $6000 lower than the car function, as the intangible cost of the high-efficiency gasoline truck is this much lower than the high-efficiency car in CIMS ($301). The shape of these curves indicate that consumers perceive HEV intangible costs to be very high when HEVs first enter the market, declining substantially as they diffuse. As discussed in Section 1.3, the diffusion of innovations theory predicts this pattern, where intangible costs are highest in an 'innovator' based market, decreasing rapidly in transition to an 'early-adopter' market.

Table 24: Intangible Cost Parameters for CIMS (*i, A,* and *K*) - Old Versus New

	Old Estimate	New Estimate			
Vehicle Technology	Fixed Intangible Cost	Fixed Intangible Cost	Variable Intangible Cost (t = 0)	'A' Parameter	'K' Parameter
Car – High Eff	$6555	$6555			
Car – Low Eff	-$3420	-$3420			
Car – HEV	$4849	$5858	$35,359	0.3992	64.2241
Truck - High Eff	$301	$301			
Truck - Low Eff	-$10,325	-$10,325			
Truck – HEV	-$146	-$396	$36,985	0.2399	68.1411

Figure 33: Declining Intangible Cost Curve – HEV Car and Truck



4.1.3 Market Heterogeneity (*v*)

With *i* and *r* estimated, I was then able to calculate the *v* parameter, which represents market heterogeneity in the CIMS model. This procedure is represented by Equation 18 (restated Equation 10),

$$\frac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}} = \frac{(LCC_j)^{-v}}{\sum_{k=1}^{K} (LCC_k)^{-v}} \qquad \text{Equation 18}$$

Which equates the multinomial logit function used to estimate choice model coefficients with the market share algorithm in CIMS. LCC_j is the life-cycle cost of the technology, and V_i is the total utility of the technology. I used the Solver function in Excel to find a *v* value that minimized the difference between the vehicle market share predicted by the joint choice model (Equation 5) and the CIMS function (Equation 1). Using the 12 vehicle specifications from Table 22, *v* was calculated to be 5.3 for the Canada model, and 5.7 for the California model. The current CIMS *v* is 10, which underestimates the heterogeneity of the new passenger vehicle market. Previous EMRG vehicle choice studies also estimated lower *v* parameters for the vehicle node, ranging from 2.4 to 5.2 (Eyzaguirre, 2004; Horne et al., 2005; Mau, 2005).

4.2 Improved CIMS

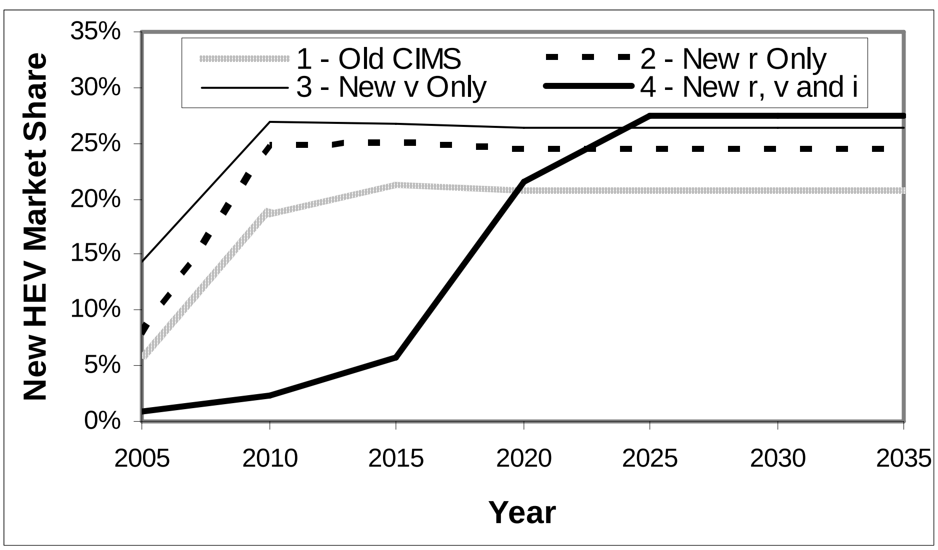
Adding the three new behavioural parameters to CIMS substantially changes HEV market share forecasts. Figure 34 depicts the shifts made by altering each parameter. Simulations with the old parameters (*r* = 30%, *i* = \$4849, and *v* = 10) predict 2005 HEV new vehicle market share to be 5%, rapidly peaking and stabilizing at about 20% in 2010, under business as usual (BAU).[15] This forecast is unrealistic for two reasons: 1) the observed 2005 HEV market share in Canada was only 0.17% and 2) most informed HEV studies do not forecast such high and rapid penetration of HEVs (e.g. Greene et al., 2004; J.D. Power and Associates, 2005).

Before adding all the new parameters to CIMS, I first tested the influence of each new estimate on market forecasts. Decreasing the *r* parameter to 21.6% increases the HEV penetration trajectory by 2-5 percentage points (curve #2). This increase was expected, as most of the relative costs of HEVs (higher capital cost) are borne in the short term, while the relative benefits (fuel savings) are received throughout the life of the vehicle. With a lower *r* value, these ongoing benefits are discounted at a lower rate, while the up front costs remain the same, and HEVs thus appear to be more desirable to consumers. Decreasing the *v* parameter to 5.3 (estimated with the Canada joint model) increases the HEV market trajectory by about 8 percentage points (curve #3). Increasing

[15] BAU refers to a run of a policy simulation model in the absence of any policy. This is the baseline that policy simulations are compared to.

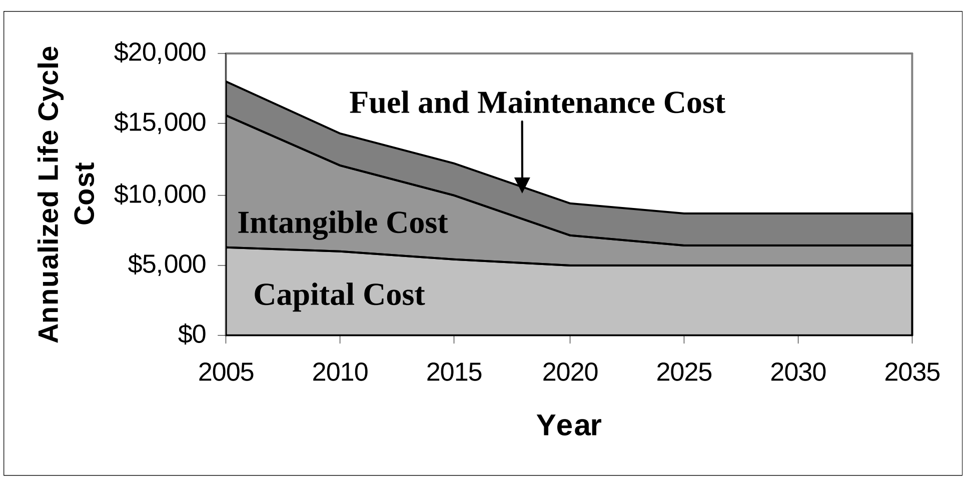
market heterogeneity indicates that more consumers are willing to adopt a new technology even when it has a higher lifecycle cost (LCC) than alternative technologies. Inputting only the dynamic intangible cost function without adjusting *v* yielded an unrealistic forecast, as HEV penetration remained near-zero for the entire simulation period (0.03%-0.12%, not shown). This finding demonstrates the importance of calibrating the *v* parameter using the same choice model used to estimate the *i* function. With an inappropriately high *v*, the initially high *i* value ($41,217) could not break out of a low market share to set the neighbour effect (declining intangible cost function) into motion. Thus, it can be seen that the *v* parameter can highly influence preference dynamics in CIMS.

Figure 34: CIMS HEV Forecasts with New Behavioural Parameters



The last market share curve of Figure 34 (#4) includes all three new behavioural parameters. This represents the ‘new’ CIMS used in this study. Adjusting the *v* parameter allows a more realistic penetration pattern, starting at 0.9% in 2005, and rising at an increasing rate to 27% in 2025. Note that this simulation uses gasoline prices predicted by Natural Resources Canada (decreasing from $0.84/Litre in 2005 to $0.65/L in 2020), and dramatically different price assumptions could produce different outcomes. For comparison, the National Energy Modelling System (NEMS), a major US energy-economy model, forecasts a similar market trajectory for HEVs (Energy Information Administration, 2006). However, NEMS predicts a linear increase in adoption over a 20 year time horizon, whereas the improved CIMS forecast resembles the s-curve shape predicted by the diffusion of innovations theory (Section 1.3). Because this diffusion curve is empirically informed, and looks realistic, I am confident that the addition of these three parameters is a substantial improvement to the CIMS model. Figure 35 depicts how the LCC of HEVs breaks down in the 'new' CIMS model over the BAU simulation. Initially, 52% of LCC is composed of intangible cost, gradually decreasing to 15%. This decrease is the primary driver of the increased adoption of HEV in the simulation forecasts. Capital and fuel costs also decrease, but to a much smaller degree.

Figure 35: Breakdown of HEV Life Cycle Cost Dynamics in New CIMS (BAU)



4.3 Uncertainty in CIMS: Sensitivity Analysis

A sensitivity analysis was conducted to assess how uncertainty in the three behavioural parameters influences the outputs of CIMS. First, I characterized the uncertainty in the *r* parameter resulting from two uncertain inputs: capital and fuel cost coefficients from the choice models. A Monte Carlo simulation was conducted (following Section 3.5.2), yielding the probability distribution function in Figure 36. The maximum likelihood estimate (MLE) of 21.6% is fairly certain, with a reasonably distinct distribution range of 19-25%. I tested the sensitivity of CIMS to this confidence range by running BAU with high and low *r* values. The resulting variation is depicted in Figure 37, where HEV market share forecast is insensitive to uncertainty in *r*. Thus, I am not particularly concerned about uncertainty in *r*.

Figure 36: Monte Carlo Simulation –Discount Rate Estimate

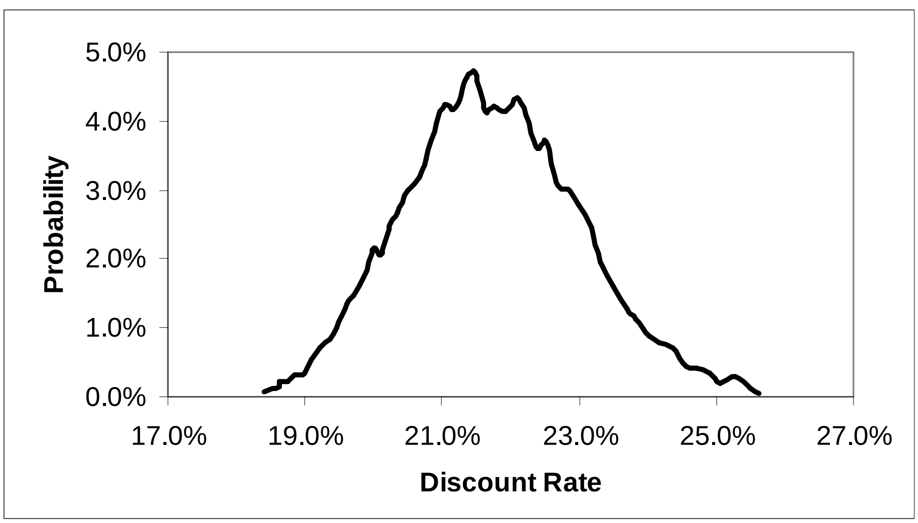
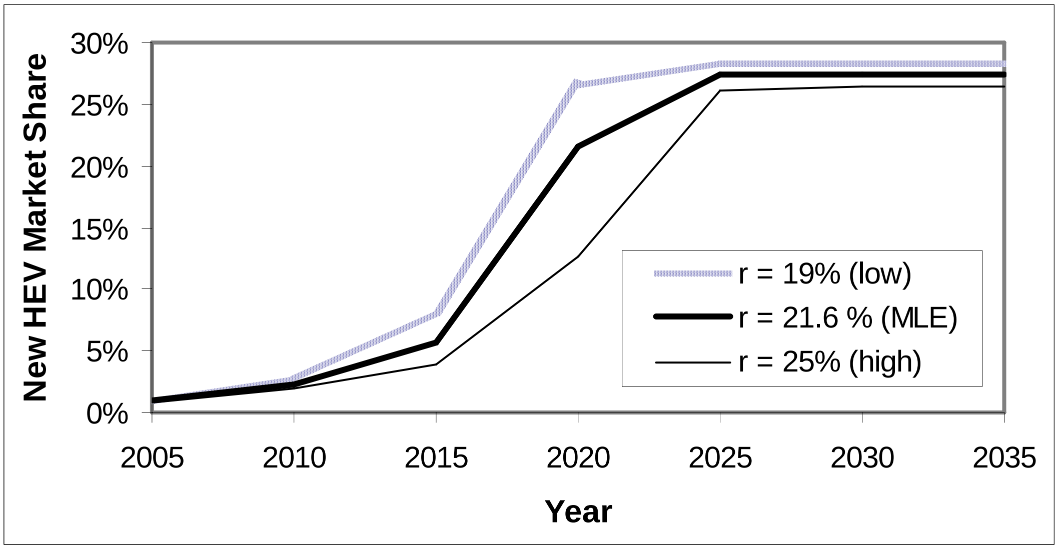
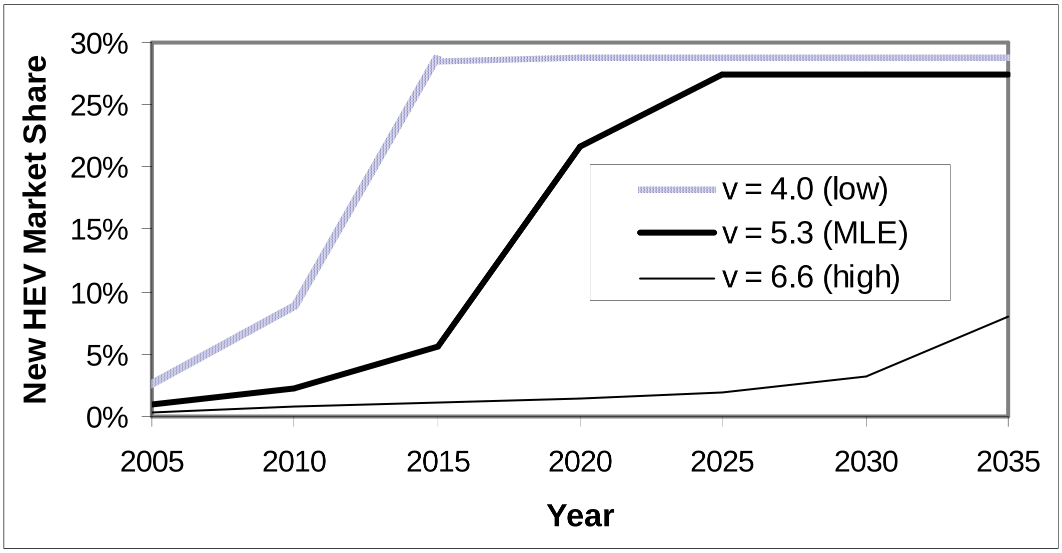


Figure 37: Sensitivity Analysis of '*r*' in CIMS



Next, I assessed the sensitivity of CIMS to variation in the *v* parameter. It was not feasible to derive a probability distribution for *v* due to its complex estimation procedure. Instead, I informally assigned high and low values using my own judgement. I varied the MLE *v* until a noticeable sensitivity was observed, which was about 1.3 in either direction. Figure 38 indicates that the new CIMS is significantly sensitive to variations in *v*, as an increase of 1.3 prevents HEVs from breaking out of a low market share, or 'crossing the chasm', within the simulation's time frame. A slight change in the opposite direction causes HEVs to infiltrate the market 5-10 years earlier. Such a sensitivity to *v* has not been observed with technologies in the old CIMS. This increased sensitivity stems from the new intangible cost specifications, as the *v* parameter has a high degree of influence when intangible costs are high. A slight variation in *v* can substantially change the timing of HEVs 'crossing the chasm' in the simulation. Thus, it is very important to appropriately adjust *v* when entering intangible cost dynamics in CIMS.

Figure 38: Sensitivity Analysis of '*v*' Parameter in CIMS



The final and most complex sensitivity analysis was conducted with the declining intangible cost function. Figure 39 depicts the Monte Carlo probability distributions of the four intangible cost estimates in Figure 32. The distribution ranges are quite diffuse for the 0.17% scenario (+/- $15,000) and 3.0% scenario (+/- $5,000), and relatively distinct for the two SP-based estimates (+/- $500). I used the high and low values of these ranges to estimate 'high cost' and 'low cost' intangible cost functions (Figure 40). I then conducted a sensitivity analysis with these variations (Figure 41), first without re-estimating the *v* parameter. The low cost scenario substantially increased HEV market share forecasts for all years. In contrast, the high cost scenario substantially reduced HEV market share for all years. I then repeated this sensitivity analysis, re-estimating the *v* parameters to correspond with the new *i* functions. The resulting adoption curves were surprisingly similar for the high cost (v = 4.7) and low cost (v = 10) sensitivity scenarios. This finding again illustrates the importance of correctly calibrating the *v* parameter to the dynamic intangible cost function.

Figure 39: Monte Carlo Simulation - Intangible Cost Estimates

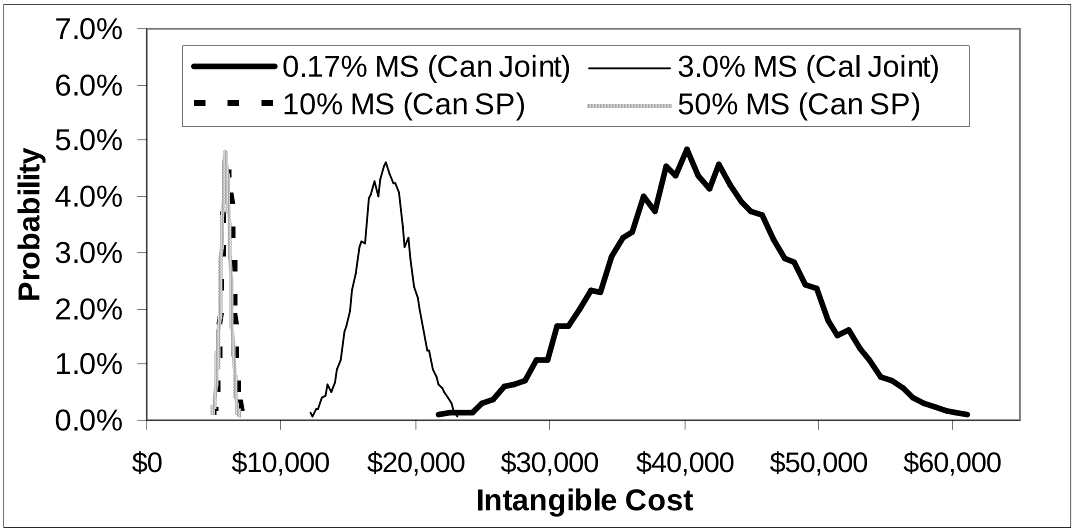


Figure 40: Variations of Intangible Cost Function – 'High Costs' and 'Low Costs'

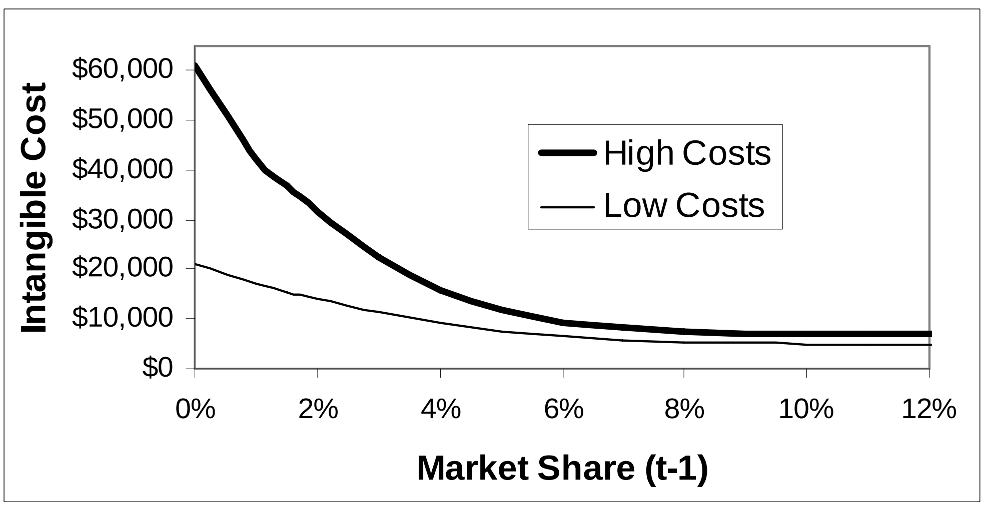
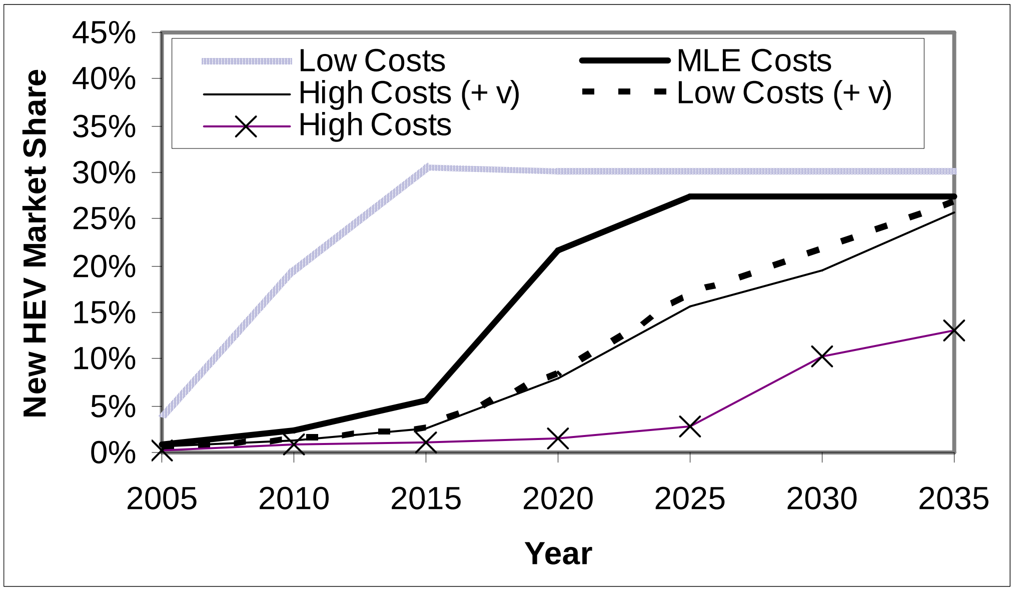


Figure 41: Sensitivity Analysis of Intangible Cost Function in CIMS



In summary, this sensitivity analysis indicates that HEV forecasts in CIMS are relatively robust to uncertainty in the *r* parameter, and significantly sensitive to uncertainties in *v* and the dynamic intangible cost function. However, it was difficult characterize uncertainty in the *v* and *i* in isolation, as the *v* estimate is highly dependent on the starting *i* value. When *v* was re-calculated for different intangible cost estimates, HEV forecasts in CIMS were much less sensitive. In any case, this uncertainty should be acknowledged when conducting policy simulations.

4.4 Policy Simulations

As the final stage of this study, I used the improved CIMS model to conduct simulations of four climate change policies in the transportation sector: 1) a carbon (or gasoline) tax, 2) an HEV subsidy program, 3) a vehicle ‘feebate’ program, and 4) a vehicle emissions standard (VES). Following the policy typology presented in Chapter 1, the first three policies are classified in the financial incentives and disincentives categories, while the VES represents a market based, artificial niche market regulation. I did not simulate examples of voluntary programs or command and control regulations.[16]

As previously noted, this analysis was conducted with a simplified version of the CIMS passenger vehicle sector. Only conventional gasoline vehicles and HEVs were specified, and many alternative fuel technologies have been excluded, such as electric, hydrogen fuel-cell, diesel, methanol and ethanol vehicles. Because intangible cost dynamics have not yet been estimated for these other technologies, it would have been inappropriate to compete them with HEVs. However, this simplified model is not overly unrealistic, as HEVs have so far proven to be the most popular of new low-emissions vehicle technologies, and thus have high potential as a means of technological change (in the short term, anyway). In addition, this analysis only simulated the Ontario region in CIMS. CIMS specifies the transportation sector exactly the same for each provincial region, so results from this analysis can easily be scaled up to apply to all of Canada. In any case, this policy simulation was primarily intended to illustrate the capabilities of the improved CIMS model, and should not be regarded as a formal policy analysis.

4.4.1 Carbon Tax (Gasoline Tax)

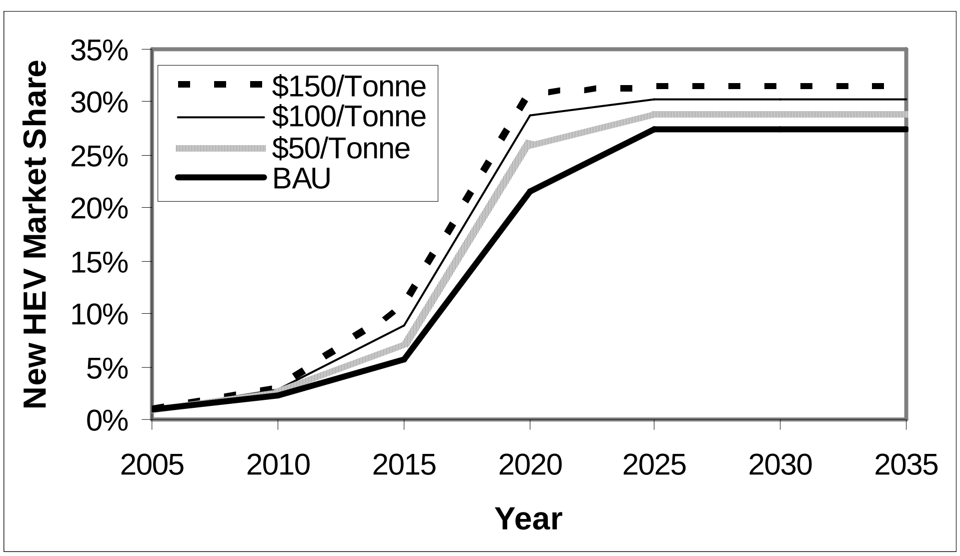
The first simulated policy was a carbon tax, which sets a tax rate per tonne of CO_2 emitted to account for the environmental costs of products and services. This policy has received much attention in the international community as a means of abating global emissions. Such a tax would largely be borne by consumers, providing incentive to reduce energy consumption or shift towards low-emissions technologies and forms of

[16] As discussed in Chapter 1, voluntary programs are expected to have little effect on technological change. I also did not explore command and control regulation due to its political unpopularity in respect to climate change policy.

energy. This tax would be perceived by vehicle users as an increase in vehicle fuel prices in proportion to their carbon content. I simulated three tax levels: $50, $100 and $150 per tonne, corresponding to gasoline price increases of gasoline taxes of about 12, 24, and 36 cents per litre. Each tax is assumed to by implemented completely in year 2005 of the model simulations.

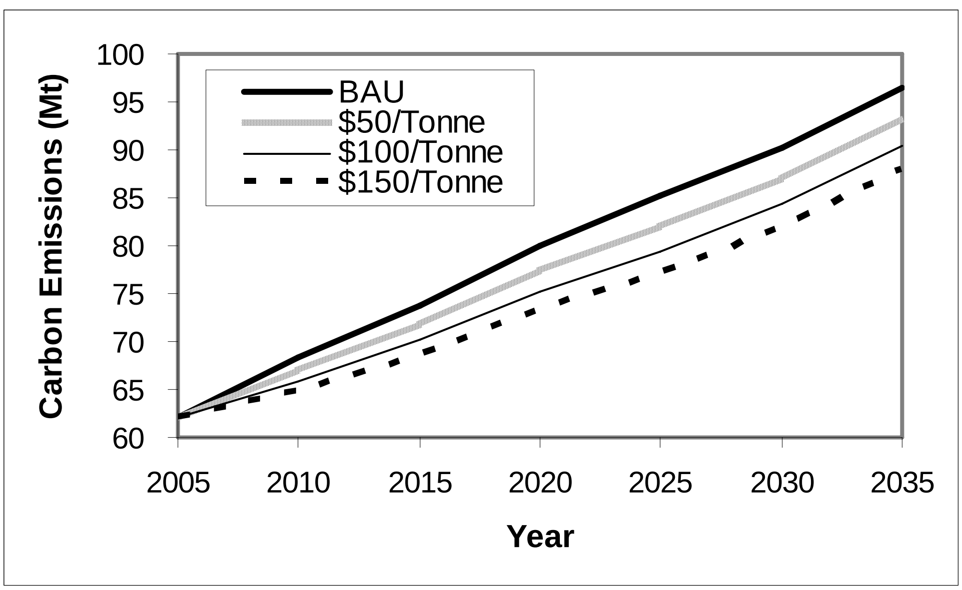
The HEV market share forecasts in Figure 42 indicate that the new CIMS is insensitive to the carbon taxes, particularly in the first 15 years. There are two main reasons for this insensitivity. First, the carbon taxes increase the operating costs of all gasoline vehicles, conventional and hybrid-electric, so the relative difference is slight. Secondly, the high initial intangible costs used in the new CIMS (52% of life-cycle cost) indicates that consumers are highly influenced by non-financial attributes until HEVs reach substantial market penetration. As shown in Figure 35, as intangible costs decline, the influence of fuel and maintenance costs increase (from 14% to 27% of life-cycle cost)

Figure 42: HEV Market Share Forecasts in CIMS – Carbon Taxes



Despite the insensitivity of HEV sales, Figure 43 shows that taxes are forecasted to decrease transportation emissions in Ontario. For example, the $100/tonne tax scenario forecast has 6.7% lower GHG emissions in 2025 than BAU. This reduction is largely caused by shifts in the transportation sector unrelated to HEV sales, such as mode switches from single occupancy vehicles to high occupancy vehicles and transit options. In summary, it appears that a carbon or gasoline tax may effectively abate GHG emissions, but may not be as effective in promoting the diffusion of new low-emissions technologies. The reliability of this conclusion, however, depends on the accuracy of the behavioural parameters in CIMS reflecting commuter choices between transit, single-occupancy and high-occupancy vehicles, which have not been improved in this study.

Figure 43: Ontario Transportation Sector Emissions Forecasts – Carbon Taxes



4.4.2 HEV Subsidy

The second policy investigated was a subsidy, where the government offers fiscal incentives to promote the adoption of low-emissions technologies. Several provinces have offered HEV subsidies in Canada, including British Columbia and Ontario. Subsidies typically take the form of rebates or tax breaks, ranging up to $3000 in value. Of the Canadian HEV owners surveyed in this study, nearly 50% reported receiving a subsidy, ranging in value from $500-$3000. I simulated several subsidy levels ($1000, $3000 and $5000) by reducing the capital cost of HEVs in CIMS. Although the Canada SP model detailed in Section 3.2.2 indicated that consumers may perceive subsidies to have 4-44% less value than an equivalent decrease in capital cost, there was substantial uncertainty in these estimates. Thus, I equated a subsidy with equal capital cost savings.

Figure 44 depicts the impacts of these policies on HEV market penetration. Sales are insensitive to subsidy level over the first 5 years, but a significant impact is seen after this point. Subsidies appear to have little effect when the initial intangible cost of the subsidized technology is very high. However, as the neighbour effect reduces intangible costs beyond 2010, the subsidies have greater influence in promoting HEVs. Figure 45 depicts the GHG reduction forecasts, which are minimal. For example, a $3000 subsidy is forecasted to reduce 2025 emissions by 1.8%. In summary, subsidies are anticipated to be ineffective in inducing short term technological change, and decreasing long term GHG emissions. In addition, it would be very difficult to raise public funds to provide subsidies on such a large scale, which could cost $1.2 billion in a given year (if 27% of 1.5 million new Canadian vehicle sales were HEVs, and all subsidized at $3000).

Figure 44: HEV Market Share Forecasts in CIMS – HEV Subsidy

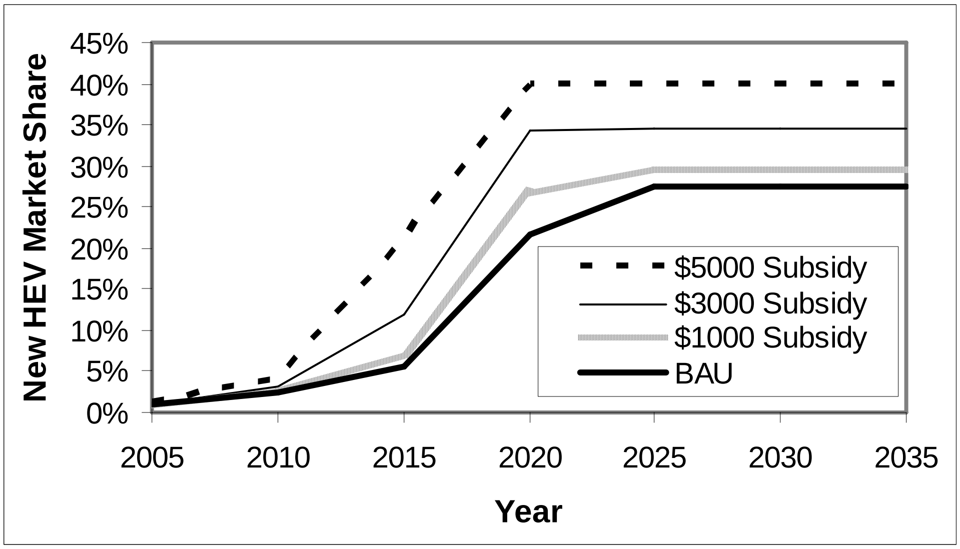
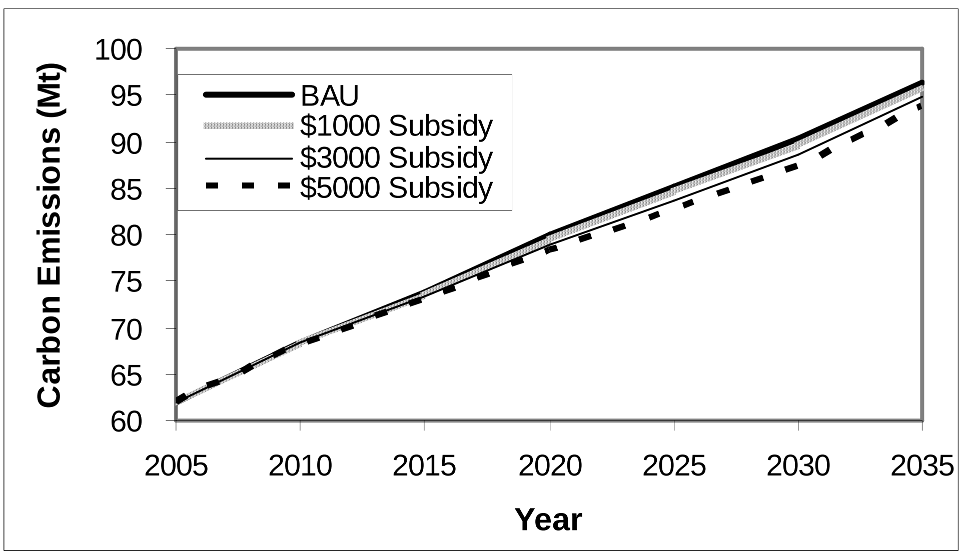


Figure 45: Ontario Transportation Sector Emissions Forecasts – HEV Subsidy



4.4.3 Feebate Program

The third policy investigated was a feebate scheme, which simultaneously subsidizes lower-emissions vehicles and taxes higher-emissions vehicles. A feebate rate is set per unit of fuel efficiency (litres per 100km), which is applied relative to a 'pivot point', or base level of fuel efficiency. Vehicles that are less efficient than the pivot point are taxed at the feebate rate, while vehicles that are more efficient are subsidized. Such a program is typically intended to be revenue neutral. Research indicates that a feebate has high potential to induce technological change in the US (Greene et al., 2005). Similarly, a study commissioned by the Canadian government found that a feebate of $1000 per litre per 100km could make substantial headway towards Kyoto abatement targets in the transportation sector (Marbek Resource Consultants, 2005). I simulated three feebate levels ($500, $1000, and $1500 per litre per 100km), using Canada's efficiency average of 9 L/100km as the pivot point. For illustration, under the $1000 feebate scenario in CIMS, the HEV car technology (5.2 L/100km) received a $3,836 subsidy, while the low efficiency vehicle (14.9 L/100km) was taxed $5,914. As in the subsidy simulations, I simply adjusted capital cost values to reflect the feebate level.

Similar to the subsidy scheme, Figure 46 shows that the feebates have little effect on HEV sales prior to 2010, again due to high intangible costs. Interestingly, an increased feebate level does not necessarily increase HEV sales for a given year. For instance, beyond 2015, HEV sales are lower in the $1500 feebate scenario than the $500 or $1000 feebate scenarios. This pattern is a result of interactions between HEV and high-efficiency vehicle technologies specified in CIMS, as both are made substantially cheaper by the feebate. Figure 47 shows that the feebates are forecasted to reduce total transportation emissions. At the recommended $1000 level, emissions are more than 15% lower than BAU in 2025. In summary, a feebate scheme is expected to substantially reduce GHG emissions by promoting low-emissions vehicles, but not necessarily HEVs.

Figure 46: HEV Market Share Forecasts in CIMS – Feebate Scheme

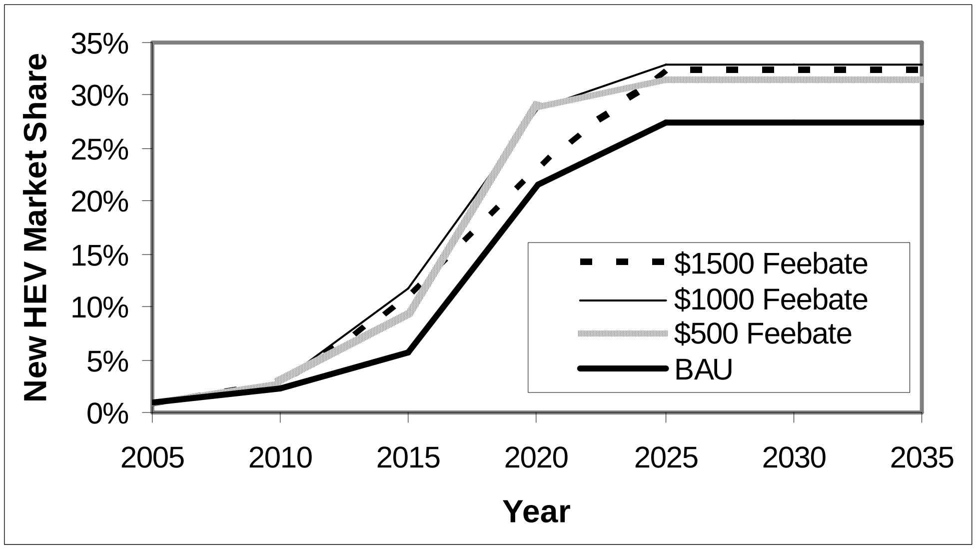
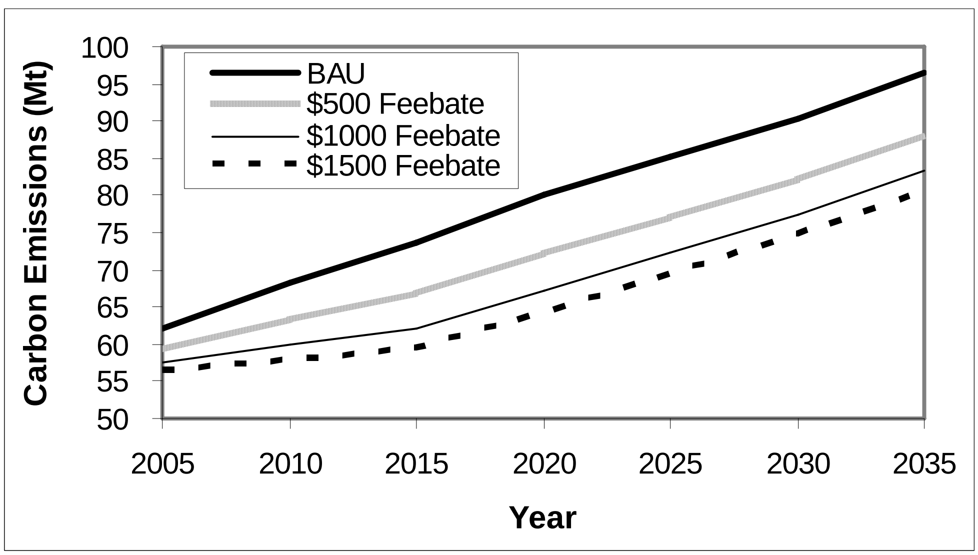


Figure 47: Ontario Transportation Sector Emissions Forecasts – Feebate Scheme



4.4.4 Vehicle Emissions Standard (VES)

The final policy simulation investigated a vehicle emissions standard (VES). I introduced this policy in Section 1.1 as a potentially effective and efficient means of inducing technological change in the transportation sector. A VES stipulates a minimum new vehicle market share of low and/or zero emissions vehicles that manufacturers must achieve by a stated year, and this minimum rises over time. Manufacturers are provided considerable flexibility in choosing tactics to meet these targets. A VES can provide an artificial niche market for low-emissions technologies until they ‘cross the chasm’, breaking into the early adopter and early majority markets where diffusion proceeds relatively autonomously. However, it is possible that some new technologies would never ‘cross the chasm’ due to unavoidably high costs. Such technologies would always require a VES type regulation to remain in the market.

A VES is difficult to simulate in CIMS because of its built in flexibility. I can exogenously specify the market share of each vehicle technology over time, but the model cannot endogenously determine how manufacturers would achieve these targets. Manufacturers would have two main levers to increase sales of low emissions vehicles: 1) decreasing financial costs, and 2) decreasing intangible costs. On the financial side, auto companies would likely implement an internal feebate-like scheme, increasing the costs of high emissions vehicles so they could subsidize the price of low emissions vehicles. On the intangible side, companies would improve the qualitative attributes of low-emissions vehicles, like style, horsepower and model variety. Automakers are also expected to engage in green and social marketing campaigns to influence consumer perceptions, as was observed during California’s VES (Kurani & Turrentine, 2004).

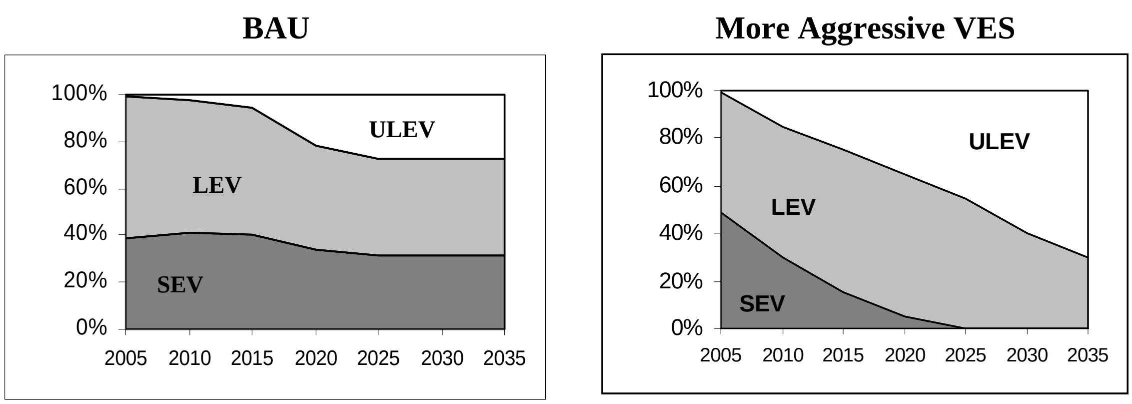
For illustration, I have simulated two VES scenarios in CIMS: ‘more aggressive’ and ‘less aggressive’ (Table 25). I specify only three classes: standard, low and ultra-low emissions vehicles (SEV, LEV and ULEV). In my simplified version of CIMS, these classes were equated to the low-efficiency gasoline (SEV), high-efficiency gasoline

(LEV) and hybrid-electric vehicles (ULEV). Typically, a zero emissions vehicle (ZEV) class would also be specified, but no such technology is included in this exercise. Both VES scenarios involved the phasing in of ULEVs, and phasing out of SEVs (Figure 48). However, the more aggressive scenario brings in ULEVs at a much faster rate.

Table 25: Vehicle Emissions Standard Scenarios Simulated in CIMS

			Minimum Market Share Requirement					
Scenario	**VES Class**	**CIMS Tech**	**2010**	**2015**	**2020**	**2025**	**2030**	**2035**
More Aggressive	ULEV	HEV	15%	25%	35%	45%	60%	70%
	LEV	High Eff	55%	65%	60%	55%	40%	30%
	SEV	Low Eff	30%	15%	5%	-	-	-
Less Aggressive	ULEV	HEV	5%	10%	20%	30%	40%	50%
	LEV	High Eff	55%	65%	70%	70%	60%	50%
	SEV	Low Eff	40%	25%	10%		-	-

Figure 48: Vehicle Emissions Standard Scenarios Simulated in CIMS



Although CIMS cannot forecast how auto manufacturers would achieve the VES requirements, it can estimate the HEV intangible cost decreases that would occur as a result of the market shares increases. Figure 49 compares the declining intangible HEV costs in BAU with the two VES scenarios. The static high-efficiency vehicle intangible cost is portrayed for comparison. Intangible costs decreased much more rapidly in the VES scenarios, becoming closely competitive with the conventional high-efficiency vehicle in about 2015. These curves indicate that up to 2010, auto manufacturers would have to make significant efforts to reduce the intangible costs of HEVs. However, if 2010 targets were met, a substantial decline in intangible costs would occur autonomously over the next decade, without additional effort required by industry. This is because the HEV technology has already 'crossed the chasm', and intangible costs begin to decline as a result of increased market share (as opposed to industry effort). The emissions forecasts of the VES scenarios are portrayed in Figure 50. The increasingly stringent technological requirements greatly reduce long term emissions in the transportation sector. By 2025, emissions are 16% lower in the more aggressive VES scenario than BAU.

Figure 49: Intangible Cost Forecasts – Vehicle Emissions Standard

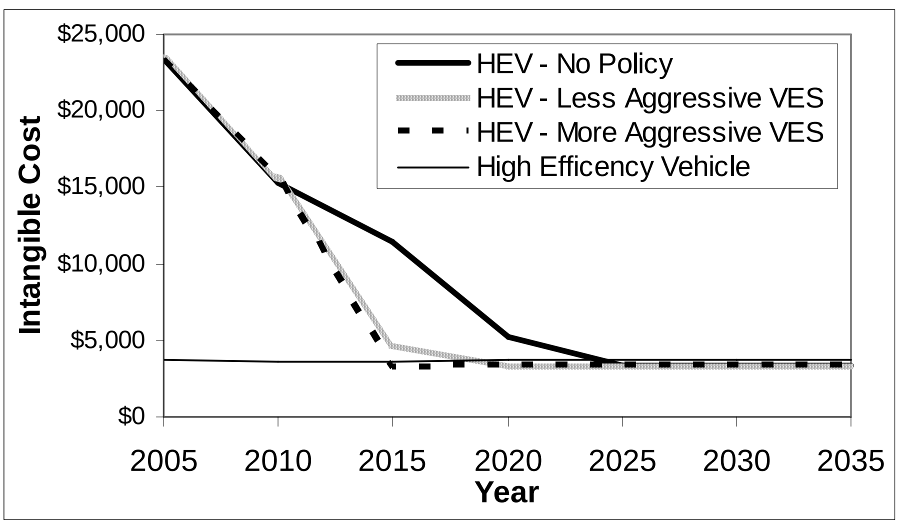
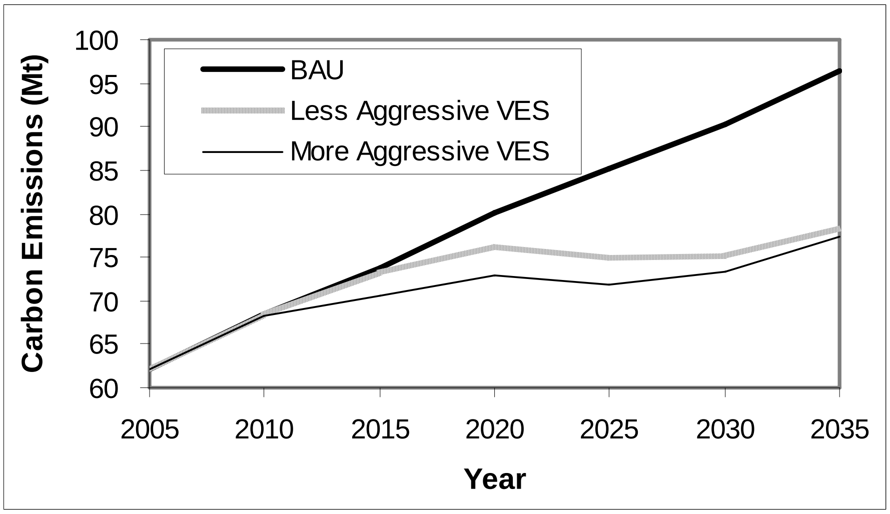


Figure 50: Ontario Transportation Sector Emissions Forecasts – Vehicle Emissions Standard



4.4.5 Policy Comparison

A summary of the four policy simulations is presented in Figures 51 and 52. As noted, these simulations were not intended as a formal policy analysis. It would be misleading to rank each policy alternative according to 'goodness' as many important factors have not been discussed, such as fairness, administrative feasibility and political acceptability. Nevertheless, the results have important implications for policymakers.

In efforts to promote the adoption of new low-emission technologies like the HEV, a policy can affect three levers: 1) the upfront financial costs (capital cost), 2) the ongoing financial costs (energy costs), and 3) the intangible costs. A carbon tax focuses on ongoing financial costs, while subsidies and feebates manipulate upfront financial costs. These policies affect intangible costs *indirectly*, where intangible costs substantially decline only when the primary lever has pushed the new technology into the mainstream market. However, as shown in Figure 35, the empirically derived intangible costs make up 52% of the perceived lifecycle costs of HEVs. Only the VES provides direct incentive for automakers to reduce both the financial and intangible costs of HEVs. Given the relatively high social discount rate, the manipulation of fuel costs has little effect on technological change. In addition, minor changes in capital cost make little difference relative to the massive initial intangible costs of the HEV. Thus, a focus on intangible costs would likely be a more efficient method of inducing HEV adoption.

Figure 51: HEV Market Share Forecasts in CIMS – Policy Comparison

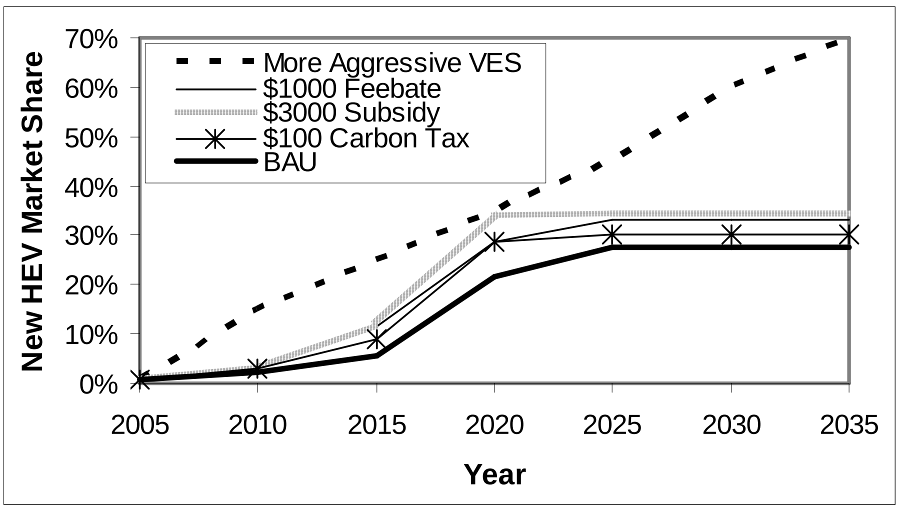
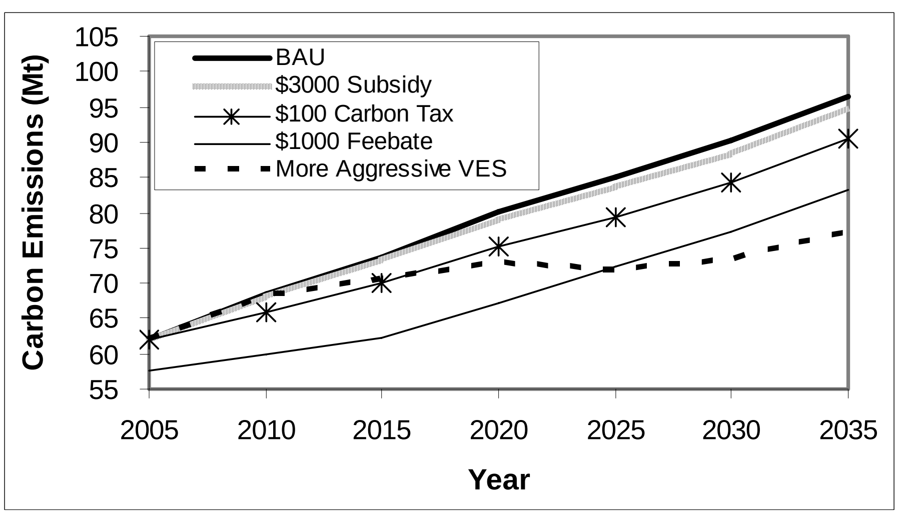


Figure 52: Ontario Transportation Sector Emissions Forecasts – Policy Comparison



CHAPTER 5 – SUMMARY AND RECOMMENDATIONS

5.1 Summary

The primary goal of this study was to establish a reliable method of empirically estimating behavioural parameters for CIMS, a hybrid energy-economy model. I sought to represent the neighbour effect in CIMS, which is the tendency for the intangible (non-monetary) costs of new technologies to decrease as they gain market share. CIMS accounts for this effect with the declining intangible cost function. Focusing on hybrid electric vehicles (HEV) as a low-emissions technology, I outline four objectives in Chapter 1:

1. Derive behavioural parameters (i, r and v) for HEVs by combining stated and revealed choice models.
2. Estimate the dynamics of the intangible cost parameter in CIMS to account for the neighbour effect.
3. Analyze uncertainty in coefficients, parameters and simulation forecasts.
4. Simulate vehicle technology policies using the improved CIMS model.

In achieving these objectives, the results are broken down into two sections: choice model results, and improvements to CIMS.

5.1.1 Choice Models and Preference Dynamics

I designed an online survey to collect both stated preference (SP) and revealed preference (RP) dynamics from samples of Canadian and Californian vehicle owners. SP dynamics were collected in a two stage process. First, respondents were randomly assigned to one of three hypothetical treatment groups, where HEV sales made up 0.17% (current), 10% (moderate) or 50% (high) of the new vehicle market. An information acceleration technique was used to describe these scenarios, presenting HEV information with hypothetical newspaper articles, advertising brochures and personal testimonials. Second, respondents completed 18 hypothetical vehicle choice sets that presented conventional gasoline and HEVs with varying levels of capital cost, weekly fuel cost, subsidy, and engine power. A series of discrete choice models were estimated from the collected data, quantifying consumer tradeoffs among vehicle attributes.

RP models were estimated from the actual purchase decisions of survey respondents. Respondents entered the year, make and model of a recently purchased vehicle, and corresponding attribute levels (capital cost, fuel efficiency, horsepower and vehicle class) were drawn from a comprehensive vehicle database. This database was also used to randomly generate non-chosen alternatives for each respondent to facilitate the estimation of RP choice models. RP dynamics were inferred by comparing choice models estimated from regions with different HEV penetration levels: Canada (0.17% market share) and California (3.0% market share).

Analysis of demographic and attitudinal data indicated that both Canada and California samples were externally valid. Discrete choice models were estimated from the SP data, RP data, and a combination of both (joint). The SP models were highly significant. Initially, a separate model was estimated for each market share treatment group, but after further analysis, the data was pooled into a single model. This 'dynamic' model indicated that the SP information acceleration treatment was effective, as respondents in the higher market share scenarios (10% and 50%) were willing to pay $1,300-$1,500 more for an HEV than the respondents in the low market share scenario (0.17%). Although the Canada SP models successfully represented the neighbour effect, they greatly overestimated the desirability of HEVs in the current market. In addition, a Bayesian analysis revealed substantial uncertainty in SP coefficient estimates.

RP choice models exhibited a high degree of multicollinearity, resulting in unreliable coefficient estimates. For example, a negative horsepower coefficient was observed, indicating negative utility for increased engine performance. The addition of 11 vehicle class constants significantly improved the explanatory power of the RP models. A comparison of regional RP models revealed that HEV intangible costs were 95% lower in California than Canada. A Bayesian analysis of RP coefficients yielded significantly more certain probability distributions than the SP models. However, the RP choice models were ultimately deemed to be unreliable due to multicollinearity.

Finally, joint SP-RP choice models were estimated using the 'sequential' technique, implanting attribute coefficients from the best SP models into the RP model, and recalibrating the vehicle class constants. The initial RP attribute coefficients were discarded. The resulting composite utility functions were highly significant, free from multicollinearity, and predicted realistic market share values. Joint coefficient estimates were nearly as statistically certain as the RP model, and far more 'qualitatively' certain.

The joint models were concluded to be the most reliable of the models estimated in this study, and were thus used for the empirical estimation of CIMS behavioural parameters.

5.1.2 Improving CIMS

The second half of this study focused on CIMS, an energy-economy policy model. The joint choice models were used to estimate the three key behavioural parameters in CIMS: the discount rate (r), the declining intangible cost function (*i, A, and k*), and the market heterogeneity parameter (v). First, r was calculated to be 21.8%, which was consistent with previous vehicle choice studies. Monte Carlo simulation characterized this parameter as quite certain, and a sensitivity analysis indicated that variations had little effect on HEV market share forecasts in CIMS.

Second, the HEV intangible cost function was estimated from choice models representing four market share scenarios: the Canada joint model (0.17%), the California joint model (3.0%), and the Canada SP model (10% and 50%). The intangible cost was estimated for each scenario, and the dynamic function was fit to these four points. The resulting function substantially changed HEV market share projections in CIMS, following an s-shaped time-dependent penetration curve predicted by the diffusion of innovations theory. HEV penetration is forecasted to begin at a realistically low market share of 0.9% in 2005, slowly building to 5% in 2015, then climbing to 27% in 2025 (for the gasoline prices in the 'business as usual' scenario). This adoption curve is largely driven by steadily declining intangible costs, which make up the majority of total life cycle cost in initial simulation years. CIMS was found to be highly sensitive to uncertainties in i estimates, but this sensitivity decreased substantially when v was re-adjusted.

Finally, I estimated a *v* parameter of 5.3, which indicates a higher degree of market heterogeneity than the value of 10 currently used by CIMS. A lower *v* indicates that more consumers are willing to adopt new technologies with relatively high lifecycle costs, thus raising HEV market share forecasts. Sensitivity analysis indicates that *v* is very closely linked with the intangible cost function, so it is very important to estimate both parameters from the same empirical source (choice model).

The improved CIMS model was then used to simulate the effects of four policies on HEV adoption and GHG emissions: 1) carbon (gasoline) taxes, 2) HEV subsidies program, 3) feebate schemes, and 4) vehicle emissions standards (VES). The VES was found to be the most effective means of promoting HEV adoption followed by the feebate and subsidy schemes. The feebate and VES also yielded the highest levels of GHG abatement. However, this exercise was not intended as a formal policy analysis, but rather as an illustration of the capabilities of the improved CIMS model.

5.2 Recommendations

5.2.1 Future Research

Previous research with CIMS recommended the use of joint SP-RP choice modelling to inform behavioural parameters in CIMS. This study has confirmed that joint modelling can be used to reliably estimate the declining intangible cost function in CIMS, as well as the *v* and *r* parameters. The resulting function is realistic, and corresponds to adoption curves observed in market research. Moreover, this study showed that intangible costs can have enormous influence in the adoption of new technologies. Thus, I highly recommend that the behavioural parameters estimated in this study be added to the formal version of CIMS.

However, intangible cost dynamics should not be specified for only one new technology in a given sector. For instance, it would not be appropriate to compete the dynamic HEV intangible costs against electric vehicles with lower, static intangible costs. Therefore, intangible cost functions should be estimated for all new vehicle technologies in the transportation sector of CIMS.[17] Unfortunately, this proposition has three main challenges. First, this HEV study was considerably complex and costly, and would not likely be replicated for other technologies. Second, joint choice models cannot be estimated for most other new technologies, as they have not yet penetrated the mass market. Thirdly, the intangible cost function estimated in this study is unique to HEVs, and could not be easily extrapolated to other technologies, particularly those that involve revolutionary shifts in technologies and infrastructure (like hydrogen-fuel cell vehicles).

Despite these challenges, I believe a solution is possible. This study has yielded important lessons about the declining intangible cost function that could be applied to any technology in CIMS. First, intangible costs are likely to be very high at low market penetration, as the market is limited to innovators, and the new technology is unknown to most consumers. Second, intangible costs decline quite rapidly as the technology progress through the innovator stage, and penetrates the early-adopter market. Simulations indicated this switch point occurred at around 3-5% market share for HEVs, where further penetration occurred relatively rapidly and autonomously due to low intangible costs. Third, there is a market share 'floor' where intangible costs cease to

[17] Well-established technologies, like conventional gasoline vehicles are not expected to have intangible costs that substantially change with changes in market share.

decline substantially, which occurred at about 10% for HEV. At this point, consumers become indifferent to increased popularity of the vehicle, and place more focus on financial savings. Considering these observations, a researcher could approximate a technology's intangible cost function by estimating four values: the initial intangible cost (at zero market share), the degree of penetration required to significantly decrease intangible costs, the market share 'floor', and perceived intangible cost at that floor. These values could be determined through literature review, expert opinion, and data from proxy technologies. Particular attention would have to be paid to revolutionary technologies, which are subject to much different barriers than evolutionary technologies. Such an estimation process would be less reliable than this empirical study, but the resulting dynamic functions would be more realistic than the fixed values currently used in CIMS.

Future research should also carefully consider the empirical estimation of the v parameter, particularly when estimating an intangible cost function. In this study, market share forecasts were highly sensitive to variations in v. Such sensitivity has not been observed in CIMS before, likely because intangible cost values are typically much smaller. Thus, if intangible cost dynamics are to be estimated for other CIMS technologies, new v parameters should also be estimated. Again, this could be done through an informal consultation of literature and expert opinion, or through a trial-and-error calibration exercise in CIMS.

I also have several recommendations for future discrete choice studies. First, the information acceleration technique used in this study proved an effective means of simulating alternate market scenarios in the Canada sample. I suspect that the use of multiple information sources (newspaper, brochure, etc) aided this success, as well as the inclusion of realistic variables in the treatment, such as vehicle class availability. However, this same treatment was not successful with the California sample. I suspect that this difference was a result of poor quality data collection, as Californian respondents generally dedicated much less time to complete the survey. Therefore, while I recommend this scenario treatment technique for future studies of this nature, researchers should make efforts to recruit only ‘high quality’ samples where respondents are more likely to thoroughly complete the survey.

Second, future SP choice studies could be constructed to a have higher degree of realism than the SP models in this study. For instance, choice sets with 3-4 vehicle alternatives would likely produce coefficients with more certainty and explanatory power than binary choice sets. In addition, SP alternative specific constants representing low penetration technologies (like HEVs) could possibly be calibrated to reflect real market share values using a weighting technique. Such a technique could serve as a crude version of the joint estimation technique used in this study.

Third, future choice studies at EMRG could experiment further with more advanced specification techniques. For example, the mixed-logit model may be more appropriate than the multinomial logit for estimating joint choice models (Brownstone et al., 2000). In addition, the nested logit approach can represent hierarchical decisions (Hensher et al., 2005), and could be explored as a means of estimating behavioural parameters for an entire node of CIMS with a single model.

Finally, future choice studies could further investigate the inclusion of demographic and attitudinal data in choice models. Demographic variables are commonly specified in choice models, but are not typically utilized in studies conducted for CIMS, due to its aggregated nature. However, the exclusion of important demographic variables could lead to distorted error variances and inflated constant estimates. In addition, attitudinal data could add to the explanatory power of choice models (Ewing & Sarigollu, 2000), and may be particularly useful for comparing choice models estimated from different regions (such as Canada and California).

5.2.2 Policy

This study also yielding findings that have direct implications for policymakers. Three primary levers where identified that a policy can target to induce technological change: 1) upfront capital costs, 2) ongoing costs, and 3) upfront intangible costs. Subsidy and feebate programs target the first component, while carbon taxes target the second. However a market based policy, like the vehicle emissions standard (VES) encourages manufacturers to seek the most efficient blend of all three levers. This study revealed that a focus on intangible costs can be one of the most efficient policy levers because 1) they start high, 2) they decrease more substantially than other costs as market share increases, and 3) this decrease can build momentum and potentially become self-sustaining at a certain switch point. Thus, this study provides support to the notion that artificial-niche market style regulations can be more economically efficient than other methods of inducing technological change.

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APPENDICES

Appendix A: Online Survey

emrg Vehicle Choice Survey

Welcome to the Vehicle Choice 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).

emrg

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 specially 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.

This survey includes 5 sections:

1. Characteristics of Your Current Vehicle
2. Information about Hybrid Electric Vehicles
3. Your Vehicle Choices
4. Your General Preferences
5. Information about Yourself

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

Your opinions and ideas are important, so please answer every question. Respondents so far have taken **20-30 minutes** to complete the survey. You may withdraw your participation at any time. You may register any complaints with the Director of the REM department at Simon Fraser University as shown below:

Bill de la Mare, 8888 University Way, Burnaby, British Columbia, V5A 1S6, Canada.

Logging in to our survey indicates that you understand and are in agreement with our confidentiality provisions. By completing this survey, you are consenting to participate in the study. To find out how you can obtain the results of this study, please email: vehicle@sfu.ca.

Please do not use your browser's back button during the survey.

I Agree

Welcome to the Vehicle Choice Survey

5% Complete

1. Are you 19 years of age or older?

Please select...

2. Have you or your family purchased a new vehicle in the past 5 years, where you played a significant role in the purchase decision?

Please select...

3. Is this vehicle model year 2002 or later?

Please select...

4. Does this vehicle run on gasoline?

Please select...

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

Please select...

6. Do you live in an urban centre with a population greater than 250,000?

Please select...

Submit

Section 1 — 10% Complete

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

1

Submit

Please enter the year, make and model of your vehicle below. This vehicle will be referred to as your PRIMARY VEHICLE.

2. Please indicate the year, make and model of this vehicle:

Model Year: 2003

Manufacturer: LINCOLN

Model: LS

Submit information above

If your vehicle is not listed above, please fill in all of the information below:

Model Year:

Manufacturer:

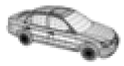
Model:

Submit Manual Entry

The next 8 questions refer to your primary vehicle.

3. In which of the following 11 categories would you classify your primary vehicle?


Sub-Compact Car

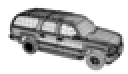

Compact Car

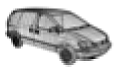

Midsize Car

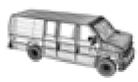

Large Car

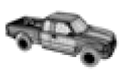

Small SUV

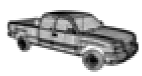

Medium SUV


Large SUV


Minivan


Large Van


Small Pickup


Large Pickup

4. What was the purchase price of your primary vehicle when you or your family bought it?
   Please use your best estimate

   $

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

   $

6. On average, what are the fuel costs of this vehicle?
   Please use your best estimate.

   $ per Week

The next four questions are not required for this survey. Please use your best estimate if you have this information.

7. What was the price of gasoline in your area the last time you bought gas? Please use your best estimate. Leave blank if you don't know.

   [ ] dollars, [ ] cents **per** [Litre ▾]

8. On average, what is the fuel economy of your vehicle? (Example: 15 miles per gallon, or 10 litres per 100km) Please use your best estimate. Leave blank if you don't know.

   [ ] [Litres per 100Km ▾]

9. What is the horsepower (HP) rating of your vehicle's engine? Please use your best estimate. Leave blank if you don't know.

   [ ] HP

10. On average, how far does your vehicle get driven every year? Please use your best estimate. Leave blank if you don't know.

   [ ] [Km ▾]

[Submit]

Now think back to when you or your family purchased your primary vehicle. Imagine that the vehicle you chose was not available. Also imagine that you were restricted to choosing from a specific vehicle class. Please use a realistic budget when considering the following questions:

11. If your primary vehicle choice had not been available, and you were restricted to choosing a vehicle from the subcompact or compact car class, which model would have been your most likely choice?

   Manufacturer: [Please Select... ▾]

   Model: [▾]

12. If your primary vehicle choice had not been available, and you were restricted to choosing a vehicle from the midsize or large car class, which model would have been your most likely choice?

Manufacturer: Please Select...

Model:

13. If your primary vehicle choice had not been available, and you were restricted to choosing a vehicle from the SUV or Van class, which model would have been your most likely choice?

Manufacturer: Please Select...

Model:

14. If your primary vehicle choice had not been available, and you were restricted to choosing a vehicle from the pickup truck class, which model would have been your most likely choice?

Manufacturer: Please Select...

Model:

15. If your primary vehicle choice had not been available, and you were restricted to choosing a hybrid-electric vehicle, which model would have been your most likely choice?

Choose One:	Manufacturer	Model
☐	HONDA	CIVIC HYBRID
☐	HONDA	INSIGHT
☐	TOYOTA	PRIUS
☐	I Don't Know	

40% Complete

Section 2: Information about Hybrid Electric Vehicles

This section illustrates a hypothetical scenario, where 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.

In this scenario, 5000 of the 1.5 million vehicles sold last year were hybrid electric vehicles. This means that 1 out of every 250 new vehicles sold is a hybrid, or 0.3% . The sources below contain information about hybrid electric vehicles in this hypothetical scenario.

Carefully and thoroughly read through these sources by clicking on each of the icons below. Feel free to browse for as long as you like. Immerse yourself in this hypothetical scenario to the best of your ability.

This section sets the stage for the next one.

Please click on the following icons to view the material before going to the next section.

News Article	**Brochure**	**Personal Testimony**	
		Friend	**Stranger**
 "Hybrid Sales Taking Off"	 "Hybrids: Welcome to the Future"	 "I'm not so sure about hybrids"	 "Hybrids are great fun!"

NEXT >>

Personal Testimony

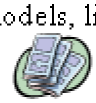
You think back to a recent conversation you had about hybrid electric vehicles…

Stranger: "I took one for a test drive, and it was great fun!"

I don't own a hybrid, but I took one for a test drive at the dealership last week. It felt really high-tech, like a car of the future. The system combines a gasoline engine with a battery-powered electric motor. It was smooth and quiet, and the car automatically knew when to start up the gas engine and when it could just run on electricity. Super cool!

Performance wise, it was just like a normal car – same acceleration and control. And I really like the idea of saving money on gas while helping the environment. I am really tired of air pollution.

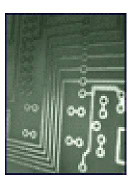
I really enjoyed the ride, and I think I might buy one as my next vehicle. I would like to be the first on my block to own one. However, it would be nice if they came in more models, like a pickup truck or minivan.



Manufacturer Brochure

You think back to a recent brochure you read about hybrid-electric vehicles …

Hybrid Electric Vehicles: Welcome to the Future



Introducing our new hybrid electric vehicles: the cutting-edge of transportation. Our hybrids replace convention with fresh thinking and innovative design.

Our hybrid electric vehicles use technology with a conscience. The gas/electric hybrid engine is exceptionally efficient, cutting pollution while saving you money. It is the easy way to help reduce air pollution and avoid climate change. Plus you spend half as much time and money at the fuel pump

The hybrid is everything a vehicle should be: powerful, responsive, accommodating, safe, and reliable. All this and you never have to plug it in for recharging. If you want to make a difference in your environment and pocketbook, visit your local dealership.

Newspaper Article

You think back to a recent brochure you read about hybrid-electric vehicles …

Hybrid Electric Vehicle Sales Taking Off: 1 out of 250 New Vehicles Sold is a Hybrid

By Suzanne Johnson

As hybrid car sales are heating up, the car market is being shaken up.

High gas prices and good word-of-mouth are prompting more drivers to try hybrid cars, which combine gasoline engines with battery-powered electric motors. By the end of last year, 1 out of every 250 new vehicles sold was a hybrid. If you are a city-dweller, you probably have seen a few hybrids around.

Hybrid vehicles are good for the earth because they suck up less gas and spit out less pollution. Likewise, hybrids are also good for our wallets, as they can cut the gas bill by up to one half, and are often eligible for government subsidies.

However, being an environmental trailblazer isn't cheap. Hybrid cars can cost substantially more than comparable conventional cars. Despite ultra-impressive gas mileage, you may have a tough time making up the price difference at the pump. Plus, this new technology is still only available in a few smaller models, which may put off families and more image-conscious buyers.

Cities across the country are grappling with the challenges of poor air quality and growing emissions of global warming gases. Driving a hybrid-electric vehicle may be one way to help out, but many consumers are not willing to fork out more of their hard earned dollars.

From here, only time will tell if hybrids will become the next big technology in the vehicle market.

Section 3: Your Vehicle Choices

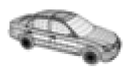
45% Complete

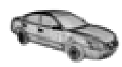
For the next section, consider that you are in the future setting as was just described.

You are looking to replace your primary vehicle, and you walk into a vehicle showroom that presents 11 different classes of vehicle. All of these vehicles are available with conventional gasoline engines, but only a few are available with hybrid electric engines.

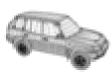
You indicated that your primary vehicle was a Midsize Car . If you were to replace your primary vehicle, which vehicle class would be your first choice? (working within a realistic budget)
Please choose one.


Sub-Compact Car


Compact Car


Midsize Car

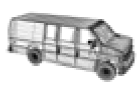

Large Car


Small SUV

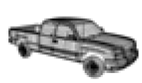

Medium SUV


Large SUV


Minivan

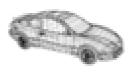

Large Van


Small Pickup


Large Pickup

Submit

The Large Pickup is not available with a hybrid-electric engine. If you were to purchase a hybrid-electric vehicle, you would be restricted to the vehicle classes listed below.
Of these vehicle classes, which would you most prefer??


Sub-Compact Car


Compact Car


Small SUV

Submit

Section 3: Your Vehicle Choices

50% Complete

Before proceeding, please read the following instructions:

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

Assume that both vehicle types are of **the same** quality to your current primary vehicle. Also assume that except for the information stated, the two vehicles are **the same**.

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

But first, think of the trip you make in your vehicle most often. Briefly describe this trip:

Origin:	
Destination:	
Duration:	
Distance:	
Landmark you pass:	

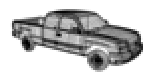
Now use this imagery to help your choices in the following vehicle comparisons. Imagine yourself driving this route in the vehicles described in each comparison, thinking about how you would feel about your purchase decision.

Proceed to next section >>

17 more comparisons to go…

Remember, both vehicle types are of similar quality to your current primary vehicle. Also assume that except for the information stated, the two vehicles are the same.

If these were the only vehicle options available to you, which one would you choose? Think about driving the vehicle along the route you described

Characteristics At any time, click on the bold blue characteristics for more information.	 Large Pickup Gasoline Vehicle	 Compact Car Hybrid Electric Vehicle
Purchase Price	$34	$51
Fuel Cost/Week	$20	$15
Pollution (Only greenhouse gas emissions)	20% Greater than current Vehicle	10% Less than current Vehicle
Subsidy on Purchase Price (Provided by the Government 6 months after purchase)	$0	$0
Car Performance (Measured in horsepower of vehicle engine)	Same as Current Vehicle	30% Less than Current Vehicle
I Choose:		

Submit

Section 4: Your General Preferences

1) When you receive information about vehicles, how would you rate the following sources?

	Very Unbelievable	Somewhat Unbelievable	Neutral	Somewhat Believable	Very Believable
Government	O	O	O	O	O
Press (Newspapers, magazines and the TV News)	O	O	O	O	O
Personal Testimony (From strangers, friends and family)	O	O	O	O	O
Advertising	O	O	O	O	O
Consumer Reports	O	O	O	O	O
Your Own Past Experience	O	O	O	O	O
Other source (Please Specify):	O	O	O	O	O

2) How important are the following attributes in your vehicle purchase decision?

	Very Unimportant	Unimportant	Neutral	Important	Very Important
Purchase Price	O	O	O	O	O
Fuel Cost	O	O	O	O	O
Pollution Levels	O	O	O	O	O
Subsidy Eligibility	O	O	O	O	O
Body Type	O	O	O	O	O
Performance/Handling	O	O	O	O	O
Comfort	O	O	O	O	O
Reliability	O	O	O	O	O
Popularity of vehicle	O	O	O	O	O
Warranty Coverage	O	O	O	O	O
Distance per gas tank	O	O	O	O	O
Engine noise	O	O	O	O	O
Interior/Luggage Space	O	O	O	O	O
Maintenance/Service Cost	O	O	O	O	O
Resale Value	O	O	O	O	O
Safety/Security Features	O	O	O	O	O
Transmission Type	O	O	O	O	O

3) Please indicate to what level you agree or disagree with the following 15 statements:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
There is not enough time in the day to get everything done.	O	O	O	O	O
I like to be the first among my friends and neighbors to own a new technology.	O	O	O	O	O
Whatever we do, the world's destiny is predetermined and history will take its course.	O	O	O	O	O
New technologies cause more problems than they solve.	O	O	O	O	O
I would be willing to spend a bit more money on a technology that is environmentally friendly.	O	O	O	O	O
	O	O	O	O	O
I rarely ever worry about the effects of pollution on myself and family.	O	O	O	O	O
I am really not willing to go out of my way to do much to help the environment.	O	O	O	O	O
I would be willing to take the bus, train, or metro to work instead of my vehicle in order to reduce air pollution.	O	O	O	O	O
I would probably never join a group, club or organization that is concerned solely with ecological issues.	O	O	O	O	O
I think that it is necessary to take steps to counteract global warming/climate change right now.	O	O	O	O	O

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The government has made significant progress in dealing with air pollution in the last 20 years.	O	O	O	O	O
I would support a government law requiring automakers to produce environmentally friendly cars.	O	O	O	O	O
I don't think the government is doing an adequate job of protecting the environment.	O	O	O	O	O
I generally don't trust what the government has to say about environmental issues.	O	O	O	O	O
The government should play a strong role in promoting environ-mentally friendly technologies.	O	O	O	O	O

Submit

About Yourself: 90% Complete

Note: Yours answers will be kept strictly confidential in accordance with Simon Fraser University Ethical Guidelines.

1. What is your age?

    Years

2. What is your gender?

    Please check the appropriate box.

    - [x] Male
    - [ ] Female

3. What is the highest level of education you have completed?

    Please check one.

    - [ ] Grade 8 or less
    - [ ] Some high school
    - [ ] High school graduate
    - [ ] Some university/college
    - [ ] University/college graduate
    - [ ] Some graduate school
    - [ ] Masters, doctoral or professional degree

4. What income category do you fit into?.

    My annual family income is:

    - [ ] Less than $20,000
    - [ ] $20,000 to $39,999

- $40,000 to $59,999
- $60,000 to $79,999
- $80,000 to $99,999
- $100,000 to $124,999
- $125,000 to $150,000
- Greater than $150,000

5. Where do you live?

   Please select the appropriate box and enter the corresponding information.

   - Canada City: [ ] Province: Please Select One
   - United States City: [ ] State: Please Select One

6. How many people are in your household?

   - 1
   - 2
   - 3
   - 4 or more

7. How many children to you have under the age of 10?

   - 0
   - 1
   - 2
   - 3
   - 4 or more

8. How many children to you have from age 10 to 18?

- 0
- 1
- 2
- 3
- 4 or more

9. When making a vehicle purchase decision, who would you normally consult from your household?

- Nobody
- Partner/Spouse
- Child
- Other

10. Thank you for completing the survey. If you have any further comments, please enter them below.

Submit

Last Step - Save your results

100% Complete

Thank you very much for participating in this study!

To find out how you can obtain the results of this study, please email: vehicle@sfu.ca.

Click here to return to the title page of the survey

Appendix B: Fractional Factorial Design

Design (Generated in SPSS)

Choice Set	CC_GAS	CC_HEV	FC_GAS	FC_HEV	SUB_HEV	HP_HEV	FP
1	3	2	2	3	3	1	1
2	2	3	3	1	3	2	1
3	2	1	2	2	1	3	1
4	1	3	3	3	2	3	1
5	1	1	1	1	1	1	1
6	3	2	1	2	2	2	1
7	1	2	2	1	3	3	2
8	2	3	1	2	3	1	2
9	3	1	3	1	2	1	2
10	2	1	2	3	2	2	2
11	3	3	1	3	1	3	2
12	1	2	3	2	1	2	2
13	2	2	1	1	2	3	3
14	1	3	2	2	2	1	3
15	3	3	2	1	1	2	3
16	1	1	1	3	3	2	3
17	3	1	3	2	3	3	3
18	2	2	3	3	1	1	3

Correlation Matrix

	CC_GAS	*CC_GAS*	*FC_GAS*	*FC_HEV*	*SUB_HEV*	*HP_HEV*	*FP*
CC_GAS	1						
CC_GAS	0	1					
FC_GAS	0	0	1				
FC_HEV	0	0	0	1			
SUB_HEV	0	0	0	0	1		
HP_HEV	0	0	0	0	0	1	
FP	0	0	0	0	0	0	1

Appendix C: Sample Demographics

Province	Canada %	2001 Canada Census
British Columbia	31%	13%
Alberta	11%	10%
Saskatchewan	2%	3%
Manitoba	5%	4%
Ontario	35%	38%
Quebec	6%	24%
Nova Scotia	5%	3%
New Brunswick	2%	2%
Prince Edward Island	1%	0%
Newfoundland	3%	2%
Territories	0%	0%
TOTAL	**100%**	**100%**

Education	Canada %	California %	2001 Canada Census
Grade 8	0%	0%	10%
Some high school	1%	0%	22%
High school grad	10%	6%	18%
Some college	27%	40%	17%
College graduate	48%	30%	30%
Some Grad school	3%	7%	0%
Grad school graduate	10%	16%	3%
TOTAL	**100%**	**100%**	**100%**

Age	Canada %	California %	2001 Canada Census
Under 20	1%	1%	24%
20-29	26%	25%	14%
30-39	34%	22%	14%
40-49	23%	26%	17%
50-59	12%	22%	13%
60 and over	3%	4%	18%
TOTAL	**100%**	**100%**	**100%**

Number of Vehicles Owned	Canada %	California %
One	38%	28%
Two	44%	42%
Three	13%	19%
Four or more	5%	10%
TOTAL	**100%**	**100%**

Year of Primary Vehicle Model	Canada %	California %
2002	27%	29%
2003	20%	19%
2004	21%	19%
2005	23%	23%
2006	9%	9%
TOTAL	**100%**	**100%**

Primary Vehicle Class	Canada %	California %
Subcompact	9%	7%
Compact	48%	43%
Midsize	7%	11%
Large Car	1%	3%
Small SUV	5%	4%
Midsize SUV	11%	15%
Large SUV	1%	4%
Minivan	14%	5%
Large Van	0%	0%
Small Pickup	1%	4%
Large Pickup	3%	4%
TOTAL	**100%**	**100%**

Income	Canada %	California %
Under $20,000	2%	3%
$20,000-$39,000	14%	16%
$40,000-$59,000	21%	18%
$60,000-$79,000	20%	20%
$80,000-$99,000	17%	16%
$100,000-$124,000	13%	13%
$125,000$-149,000	5%	6%
Over $150,000	7%	9%
TOTAL	**100%**	**100%**

Household Size	**Canada %**	**California %**
One	9%	16%
Two	32%	33%
Three	21%	21%
Four or more	38%	31%
TOTAL	**100%**	**100%**

Children 18 or Under	**Canada %**	**California %**
Zero	55%	56%
One	18%	21%
Two	18%	14%
Three	7%	5%
Four or more	1%	3%
TOTAL	**100%**	**100%**

Who is Consulted in Vehicle Purchase Decision?	**Canada %**	**California %**
Nobody	17%	30%
Spouse/Partner	71%	63%
Child	1%	1%
Other	11%	6%
TOTAL	**100%**	**100%**

Appendix D: Regional Comparison of Attitudes

A) Technology Statements

Statement	Region	Disagree	Agree	Neutral	Total
There is not enough time in the day to get everything done.	Canada	15%	67%	18%	100%
	California	16%	65%	19%	100%
I like to be the first among my friends and neighbors to own a new technology.	Canada	36%	27%	36%	100%
	California	34%	30%	36%	100%
Whatever we do, the world's destiny is predetermined and history will take its course.	Canada	56%	20%	24%	100%
	California	54%	19%	28%	100%
New technologies cause more problems than they solve.	Canada	61%	11%	27%	100%
	California	58%	14%	28%	100%
I would be willing to spend a bit more money on a technology that is environmentally friendly.	Canada	7%	61%	32%	100%
	California	9%	58%	33%	100%

B) Environment Statements

Statement	Region	Disagree	Agree	Neutral	Total
I rarely ever worry about the effects of pollution on myself and family.	Canada	70%	12%	17%	100%
	California	62%	15%	23%	100%
I am really not willing to go out of my way to do much to help the environment.	Canada	76%	6%	18%	100%
	California	68%	9%	22%	100%
I would be willing to take the bus, train, or metro to work instead of my vehicle in order to reduce air pollution.	Canada	41%	31%	28%	100%
	California	44%	30%	26%	100%
I would probably never join a group, club or organization that is concerned solely with ecological issues.	Canada	33%	39%	28%	100%
	California	37%	34%	29%	100%
I think that it is necessary to take steps to counteract global warming/climate change right now.	Canada	5%	77%	18%	100%
	California	7%	68%	25%	100%

C) Government Statements

Statement	Region	Disagree	Agree	Neutral	Total
The government has made significant progress in dealing with air pollution in the last 20 years.	Canada	41%	26%	33%	100%
	California	33%	36%	31%	100%
I would support a government law requiring automakers to produce environmentally friendly cars.	Canada	5%	83%	12%	100%
	California	10%	69%	21%	100%
I don't think the government is doing an adequate job of protecting the environment.	Canada	10%	60%	30%	100%
	California	14%	57%	29%	100%
I generally don't trust what the government has to say about environmental issues.	Canada	15%	47%	39%	100%
	California	11%	54%	34%	100%
The government should play a strong role in promoting environ-mentally friendly technologies.	Canada	2%	85%	13%	100%
	California	5%	75%	20%	100%