INCORPORATING PREFERENCES FOR PERSONAL URBAN TRANSPORTATION TECHNOLOGIES INTO A HYBRID ENERGY-ECONOMY MODEL

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ABSTRACT

Energy modelers have traditionally taken top-down or bottom-up approaches to portray the interactions between energy production and consumption, and the economy. Top-down models provide a more realistic representation of behavior and the feedbacks in an economy, while bottom-up models are better able to explicitly model technological change and technology focused policies. Hybrid energy-economy models, such as CIMS, attempt to combine these strengths, and as such are able to provide more realistic and meaningful predictions. One of the major challenges in developing a hybrid model is accurately depicting how firms and individuals will choose between technologies.

Discrete choice modeling was identified as a tool capable of meeting this challenge, because it has been specifically developed to empirically examine technology level choices and the factors that influence them. This research developed highly significant and intuitive discrete choice models for mode and vehicle choice decisions in the personal urban transportation sector. After aligning the discrete choice models and CIMS to account for minor inconsistencies, the two models were incorporated in CIMS. With the improved representation of behavior embedded in CIMS, a variety of policies were simulated to demonstrate the new capacity to model policies focused on the financial and non-financial attributes of urban transportation decisions. These simulations represented significant improvements over the initial capabilities of CIMS, and existing top-down and bottom-up models.

The improvements to CIMS have helped bridge the divide between top-down and bottom-up approaches by providing a true hybrid, which includes behavioral realism, technological detail, and macro-economic feedbacks. Although this work has identified a number of additional improvements that would each benefit the CIMS model, the existing research has successfully augmented the behavioral realism aspect of a hybrid model. Once the changes experimented with in this research have been permanently adopted, CIMS will be able to produce more accurate predictions for a more comprehensive suite of policies.

Dedication

Thanks to Mom and Dad, and Sarah for all
their support and encouragement in
everything I've set out to do.

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1 INTRODUCTION

With the Federal government's ratification of the Kyoto Protocol, Canada committed itself to reducing greenhouse gas emissions to 6% below 1990 levels, but based on Canada's Greenhouse Gas Inventory (Environment Canada, 2002), emissions were already 16% above 1990 levels in 2000, and they are projected to be 33% above by 2010. Without some sort of strong policy stimulus, it is highly unlikely that Canada will be able to close the significant gap that exists between the country's predicted emissions and its international commitments. The Federal Government's current plan to meet Kyoto commitments outlines some of those policies, and it seems probable that many of them will focus on pushing firms and individuals to make technology decisions that have lower green house gas emissions per unit of service delivered (Government of Canada, 2002). These types of policies are attractive because they reduce emissions by encouraging technological change that decouples energy use (and the accompanying emissions) from consumption, while allowing people to continue improving their standards of living. In this context, technological change is meant to encompass a broad scope of solutions including decisions between actual technologies (choosing between different types of lightbulbs for example), and also the ways in which those technologies are used (deciding between carpooling and driving alone for example). The policy challenges presented by the Kyoto Protocol will be similar to the emerging environmental issues that Canadians are likely to face in the future. As such, the challenges of greenhouse gas policy apply to the broader spectrum of environmental problems where technical change is seen as a potential solution.

Although technological change is capable of improving energy efficiency, this outcome is by no means guaranteed, and many examples illustrate how new technologies have led to increased energy consumption (more powerful vehicles, bigger refrigerators, and color televisions for example). Government may try to influence the manner in which technological change manifests itself by using tools such as information campaigns, financial incentives/disincentives, and regulations. With the exception of regulations, all of these policy levers rely on individuals and firms being encouraged (or discouraged) enough to change their technology decisions. Predicting how people will react to any influence is a highly uncertain endeavor, but an ideal model would allow the social, financial, and environmental costs associated with different policies to be accurately predicted. With this information, policy makers could compare and contrast policy alternatives and choose a package of policies that would achieve the desired changes at an acceptable cost to society. The unknown and uncertain factors inherent in any policy analysis make this level of accuracy impossible to obtain, but the modeling attempts to date have still left considerable room for improvement. More specifically, there are opportunities to better understand how technological change can be influenced by policy, and capitalizing on these opportunities will provide valuable information in Canada's search for low cost solutions to meet its Kyoto Protocol targets (and the future targets that are likely to follow).

The research in this paper focuses on this challenge of improving our capacity to model policies that influence technological change. This chapter sets the framework. Sections 1.1 and 1.2 look at existing modeling attempts to tackle this problem, and notes opportunities for improvement. Section 1.3 puts these general modeling concepts within the framework of personal urban transportation, and section 1.4 outlines the rest of the paper.

1.1 Modeling Technological Change

Historically, two approaches have been used to model the changes in energy consumption that result in part from the diffusion of new technologies. These are commonly referred to as top-down and bottom up modeling, and although neither is limited to modeling technological change, the following discussion will be focused on this topic. Top-down approaches, often advocated by economists, typically take an aggregate view of the economy, and model changes in the mix of technologies based on the historical behavior of the market. Bottom-up modeling takes the opposite approach by representing individual technologies so that changes in the technology mix can explicitly be modeled as stock turns over. Although both approaches seek to model the same systems, they often lead to significantly different predicted outcomes and costs. The diverging cost predictions are a common source of confusion, and a key issue in the top-down/bottom-up debate, because without an understanding of how the two approaches operate, the results they provide can be misinterpreted by placing them in an incorrect context.

Top down models look at the economy at an aggregated level (by sector for example), and individual technologies are not represented because the models take a broader view of energy and economic decisions. In general, top-down models are able to portray these decisions in a realistic manner (accounting for the financial and non-financial aspects of decision making), because they are at least in part based on historical data. Because individual technologies are not included, technological change cannot be explicitly modeled, and instead is commonly represented with a single parameter referred to as the rate of autonomous energy efficiency improvement (AEEI)[1]. This parameter can be estimated from actual data, but it is very difficult to isolate from other factors, and in practice AEEI is commonly based on modeler experience or intuition. The treatment of costs in top-down models sets up one of the key differences with bottom-up models, and deserves particular attention. Top-down models assume that markets are working properly, and therefore that individuals and firms are making the choices that are in their own best interests. Even though alternative technologies might have lower financial costs, they are not being chosen because they do not provide the same level of overall welfare. The parameters in top-down models also reflect an inertia to change, and as a result, any policies that cause different technology decisions generally lead to high costs (Jaccard et al., 2003).

The Intergovernmental Panel on Climate Change (2001) classifies two types of top-down models: traditional time-series econometric models, and the more recently developed computable general equilibrium (CGE) models. The main difference between these two

[1] AEEI actually defines the rate of energy efficiency improvement in the absence of price or policy signals. Even if AEEI is set to zero, technical change can still occur when these signals are present.

types is that CGE models look at the entire economy (including government spending, employment, trade-flows, and work/leisure tradeoffs), whereas time-series econometric models are focused strictly on the sectors producing, transforming, and consuming energy. Because of their more limited scope, time-series models are usually tractable enough to be estimated primarily from historical data and as such are highly representative of past experiences. In contrast, in order to reflect a broader scope of economic interactions, CGE models sacrifice some of this behavioral realism by basing parameters on consensus estimates from the literature or calibrating model performance to fewer data points (IPCC, 2001).

Despite the claims of realism, top down models are far from perfect, and two significant critiques have been leveled at their assumptions about market behavior. The first of these is that many modelers have questioned the validity of using AEEI to help represent technological change accurately (Azar and Dowlatabadi, 1999). General agreement exists that technological change will occur, but there is concern that unless energy prices are significant or specific energy efficiency policies are in place, technological change will manifest itself in characteristics other than efficiency (cars coming with additional service features for example). The second criticism relates to the assumption that firms and individuals are operating in their best interests, and the resulting conclusion that the current state of the economy is optimized. The market does not operate perfectly, and Jaffe and Stavins (1994) describe the failures that information can be underprovided because of its public good characteristics, and that potential adopters of energy efficient technologies may not be in a position to receive the benefits from that adoption. These market failures can each lead to a less than optimal allocation of goods and resources in the economy, which means that changes could be made without necessarily incurring costs. For example, Moxnes (2003) found that making less efficient refrigerators unavailable through regulation could actually lead to increased consumer welfare compared to an unregulated market.

Two additional critiques of top down models relate to the failure of their long-term predictions to account for policy and preference shifts, and their inability to effectively model technology focused policies (Jaccard et al., 2003). First, the key parameters in the top-down models are based on past behavior and experiences, and as such may not necessarily be valid if the future deviates significantly from those conditions. For example, increasing environmental pressures, and the related policy responses could lead to increasing rates of technological change in the search for solutions. As a result, historical values for AEEI would no longer be accurate, and the amount of future progress would be underestimated. The second critique stems from the high level of aggregation in top-down models. This treatment of technological detail is acceptable when the policies of interest are fiscal instruments such as economy-wide taxes, but it makes it increasingly difficult to model policies that focus on specific technologies such as regulations and subsidies.

Bottom up modelers claim their models overcome these weaknesses primarily because they explicitly represent technologies. Doing so allows them to model policies designed to encourage technological change more directly. These types of models utilize large databases to describe the technologies that are currently available and expected to be available to meet different energy demands. They operate based on demand forecasts (typically for energy services), and as new demands need to be satisfied, some algorithm decides which technologies are chosen. The market share allocation algorithms typically focus on financial costs using the social discount rate to trade-off operating and capital costs, where competing technologies are otherwise assumed to be perfect substitutes if they provide the same energy service. The social discount rate is lower than the observed rate implicit in top down models, meaning that technologies with lower operating costs, but higher capital costs become more attractive. This view of technological change leads to a faster penetration of energy efficient technologies than predicted by top-down models, and at a lower cost. An example of a bottom up model is MARKAL, which is a generic linear programming formulation for energy supply and demand that has been applied to energy-economies in over 40 countries (ETSAP, 2000). As a linear programming model, in addition to being a bottom up model, MARKAL predicts technology choices that are simultaneously optimized over all sectors and time periods[2].

Bottom up models don't suffer from the same shortcomings as top-down models because technologies are modeled explicitly, which allows their innovation and diffusion to be changed to depict different technology-focused scenarios and policies. They too have weaknesses however, and the primary critique leveled at bottom-up models is that the market share allocation algorithms do not reflect actual behavior, because although technologies may provide identical energy services, other factors influence the decision making process. By simply using financial costs, and the social discount rate to predict technology decisions, the algorithms over-predict peoples' willingness to change, leading to a gap between the actual and predicted market shares of apparently cost-effective energy efficient technologies. Jaffe and Stavins (1994) have attributed this energy efficiency gap in part to market realities, termed non-market failures, which include the efficient technologies having greater cost uncertainty[3], being imperfect substitutes, and having higher adoption costs. They also include market heterogeneity as a non-market failure, meaning that a technology's availability and cost will differ across the market. A second problem with bottom-up models is that they are commonly partial-equilibrium (as opposed to general equilibrium), meaning that they can determine the balance of consumption within sectors, but do not generally model the feedbacks between sectors (Jaccard et al., 2003). Bottom-up models are also subject to the critique that they tend to focus on technologies that offer improved energy efficiency, and commonly ignore new and emerging technologies that are less energy efficient or more energy intensive. An example of this is a model that includes a detailed representation of how the costs of wind generated electricity can decline as market share increases, but has no accounting for the similar ways in which natural gas extraction can become cheaper.

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[2] Although MARKAL is a well known, and well publicized bottom-up model, optimization models only represent a minority of the bottom-up models in use. Many are simple spreadsheet depictions of energy systems, which receive minimal discussion in the literature.

[3] The capital costs of energy efficient technologies are typically higher, and the financial savings are realized in the operating costs. The longer the lifespan of the technology, the more uncertain these savings become.

Despite these long-held critiques of both top down and bottom up models, many modelers from both camps have chosen to focus on their model's strengths instead of trying to improve on its shortcomings. Top-down models continue to provide a more realistic representation of consumer behavior, and macro-economic feedbacks, while the strength of bottom-up models is their technological detail. As a result, each approach excels at different modeling applications, while struggling with others. Top-down models are best suited for predictions of what will happen in an economy, as long as the conditions of that economy don't deviate too much from the past. They are weakest when conditions differ significantly from the past, and when policy needs to be targeted at specific technologies. Bottom-up models are best for exploring the possibilities of what could happen, identifying possible futures to aim for, and designing technology focused policies that might help achieve those futures. Because of their lack of behavioral realism however, bottom-up models are not suited for predictive tasks. Unfortunately, both types of models are often used for applications that go beyond their strengths, and as such, the predictions they offer are plagued with the problems described above.

The types of policy problems that expose these limitations are common, so instead of continuing to use models that are ill-suited to the tasks at hand, modelers must find approaches that can capitalize on the strengths of both top-down and bottom-up models. In other words, it is paramount that the modeling tools used for energy-economy analysis recognize the reasons behind the energy efficiency gap, and the fact that technological change can be dynamic. Designing models to meet these requirements leads to tools that are both behaviorally realistic and technologically explicit. This challenge is summarized by figure 1.1, which represents top-down and bottom-up models on three dimensions: technological detail, behavioral realism, and equilibrium feedbacks. A third type of model on the diagram represents a hybrid approach, which incorporates the technological detail of the bottom models, and the behavioral realism, and equilibrium feedbacks of the top-down models, and as a result, is able to address the policy problems discussed above. Recognizing these challenges is intuitively quite straight forward, but accounting for them in a modeling context can be extremely challenging, especially while striving to keep the models tractable and transparent enough to be useable in a policy analysis setting.

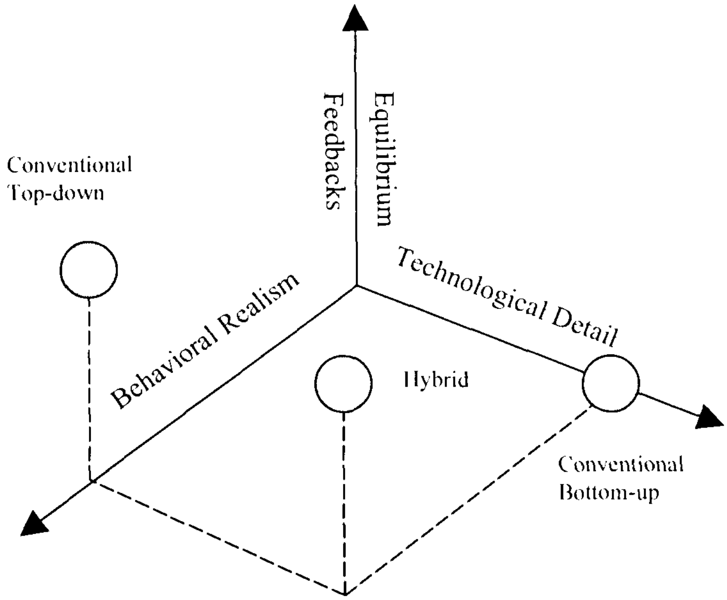

Figure 1.1 – Energy-economy model typologies (Source: Jaccard et al., 2003)

1.2 The Challenge of Hybrid Modeling

Although significant gaps still remain between top-down and bottom-up approaches, it is not as clear cut as mentioned above; some top-down models have applied increasingly disaggregated demand functions, and some bottom-up models have included more and more sophisticated technology allocation algorithms. These small steps have laid the groundwork for the development of hybrid models, and as discussed below a number of significant steps have been made starting from both top-down and bottom-up approaches. MARKAL in particular provides an excellent example of a bottom-up model that has attempted to move in the direction of hybrid models by incorporating macro-economic feedbacks, and some limited behavioral realism. MARKAL-MACRO uses the basic bottom-up model, linked to a top-down macro-economic module, and MARKAL-GP utilizes goal-programming approaches to broaden the technology allocation procedure beyond financial costs (ETSAP, 2002, and Seebregts et al., 2002). Although useful endeavors, these attempts fall short of a true hybrid model because the tradeoffs between different technology attributes are not empirically estimated, and because they still search for an optimal equilibrium, they are not behaviorally realistic.

From the top-down perspective, two different approaches have been taken to solve the weakness of not including technological detail. First, some modelers have taken an indirect approach by attempting to endogenize technological change within standard top-down models, so that instead of being a static parameter, AEEI can respond to policy and price signals. Azar and Dowlatabadi (1999) provide an overview of some of these attempts, and although they are an improvement over standard top-down models, they still fail to provide sufficient capabilities to model technology focused policies. The second approach, which moves closer to hybrid models, involves attempts to explicitly link or embed bottom-up modules within top-down models. Rivers et al. (2003) summarize the attempts of Jacobsen, Koopmans and Willem te Velde, and Bohringer, who use the results of bottom-up modules to inform the macro-economic parameters in the top-down component. Although a step in the right direction this approach fails to account for the lack of behavioral realism in the least-cost based, bottom-up modules, and as such, the information being fed to the top-down component suffers from the same shortcomings.

A prominent model that does qualify as a hybrid is the National Energy Model System (NEMS), which the Department of Energy uses to model energy policy in the United States. NEMS was developed in 1990 because the previous national modeling tool, the Intermediate Future Forecasting System, was not capable of modeling the major policies of the day such as the Clean Air Act Amendments, and the deregulation of the natural gas industry (Gabriel et al., 2001). It is difficult to provide a quick synopsis of NEMS because the modeling approach for each sector of the economy has evolved separately, but essentially it operates as a simulation model that seeks a general equilibrium within sub-modules for the different supply, demand, and transmission/conversion energy sectors. These individual solutions are linked after each iteration, and the process is reiterated until an equilibrium is reached across all sub-modules. The model contains an explicit representation of technologies, and with the exception of electricity supply, which is dictated by a linear program, technologies are allocated to reflect real market behavior. Looking at the transportation module in detail, NEMS categorizes vehicles according to manufacturer, class, acceleration, horsepower, safety, and financial costs. Despite the detailed competition structure, market share is assigned based on financial costs only, using private discount rates (EIA, 2002).

DeCanio and Laitner (1997) critique NEMS' (and other models that allocate technology market shares using similar methods) reliance on financial costs to portray realistic behavior. NEMS uses implicit discount rates ranging from 30% to 620% to represent some of the factors behind the energy efficiency gap, which DeCanio and Laitner claim over-restricts emerging energy efficient technologies from capturing market share, over-estimates costs for technological change, and limits the range of possible policy interventions. They argue that the model's reliance on discount rates to replicate market behavior results in discount rates that are too high, and propose instead that the technology decisions should be modeled using additional non-monetary technology attributes, which they believe will lead to lower estimated discount rates. Although other, non-financial, factors clearly play a role in technology decisions, the findings of Morris et al. (2002) show that Laitner and DeCanio's critiques may be somewhat unfair. Based on a direct comparison between NEMS and the US version of MARKAL-MACRO (a non-linear optimization model), NEMS predicted greater adoption of renewable electricity generation options, which are technologies that are typically more favored by traditional bottom-up models.

CIMS is another hybrid energy economy model, similar in design to NEMS in that it iteratively seeks equilibriums within each of its sectors until an overall equilibrium is obtained for each period of the simulation. Developed by the Energy and Materials Research Group (EMRG) at Simon Fraser University, CIMS will serve as the energy-economy modeling tool for this research, and for that reason is described in some detail here. CIMS utilizes an explicit representation of technologies to satisfy energy service demands that are disaggregated according to the sectors and regions of Canada (Jaccard et al., 2003). In order to tackle the problem of behavioral realism, CIMS allocates technologies according to the logistic relationship shown in equation 1.1,

$$MS_j = \frac{\left[CC_j \times \frac{r}{1-(1+r)^{-n}} + MC_j + EC_j + i_j\right]^{-v}}{\sum_{k=1}^{K}\left\{\left[CC_k \times \frac{r}{1-(1+r)^{-n}} + MC_k + EC_k + i_k\right]^{-v}\right\}} \qquad \textit{(Equation 1.1)}$$

where, MS_j is the market share of technology j, CC_j is the capital cost, MC_j is the maintenance cost, and EC_j is the energy cost. This equation contains three specific parameters (that can differ across technologies) to reflect different aspects of the decision making process that wouldn't be captured by a least-cost analysis. First, the discount rate (the r parameter) is used to represent consumer time preference in the relationship between operating and capital costs. Second, intangible costs (the i_j parameter) are used to represent the monetized value of the non-financial components of a decision. Third, market heterogeneity (the v parameter) allows CIMS to recognize that market conditions differ across the country, so even if a technology may be cheaper on average, it will be more expensive for some consumers, and therefore achieve non-negligible market share. Figure 1.2 illustrates the affect that different values of v can have on technology market shares for a simple two technology case, where the steeper curves (those with the higher values for v) indicate higher cost responsiveness, and less market heterogeneity.

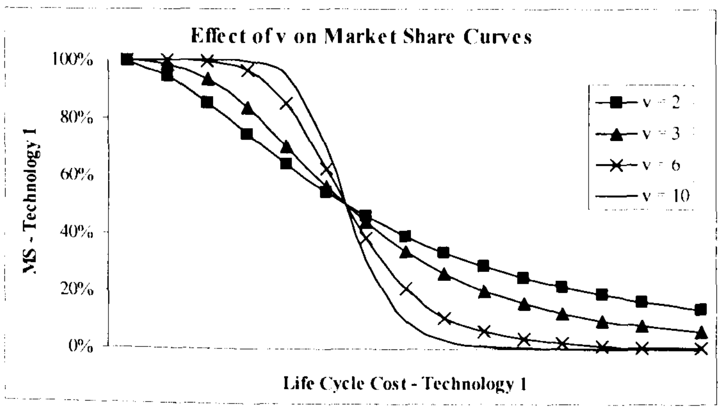

Figure 1.2 - Effect of market heterogeneity on market share predictions

In theory, this relationship for allocating market share can answer DeCanio and Laitner's critiques leveled at NEMS because the intangible parameters are included to represent the other non-financial attributes of a technology decision. In practice however, these parameters are extremely difficult to estimate, which is the same problem encountered by any attempts to model human behavior. The parameter values currently being used are based on literature reviews, meta-analysis, and expert opinion, but in many cases these estimates are modified to calibrate the model's business as usual predictions to external forecasts[4]. The problem with this approach is that the three key parameters described above can confound one another so that no unique solution exists to a calibration approach. In other words, an infinite number of v, i, and r combinations could achieve the same calibration. Unfortunately, although these different calibrations are equivalent in the business as usual case, their predictions diverge as policy scenarios diverge from business as usual, and without any empirical basis, there is no way to tell which calibrations are more accurate. Ideally the parameter values would all be empirically estimated so that analysts could be more confident in CIMS' predictions over a wide range of policy scenarios.

The challenge of finding a sound empirical basis for representing human behavior is not unique to the field energy modeling. It is a challenge faced in many other fields, and as such, each attempt to understand and model human behavior represents a potential solution that could be used with CIMS. Discrete choice models are one of these potential solutions, as they have been developed specifically to look at consumer technology choices (although not necessarily from an energy service perspective). These models generally don't possess any information about the equilibrium feedbacks present in an energy economy model like CIMS, but they do excel at predicting behavior, which is why they will be used to improve the parameter values currently used in CIMS. Section 2 discusses discrete choice models in more detail, but the general way they will be used in this research is as follows. First, discrete choice models are developed for the

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[4] See Nyboer (1997) for a more detailed discussion of the parameters used in CIMS, and Murphy (2000) for the transportation sector in particular.

technology decisions of interest so that the behavioral complexities of these decisions can be modeled using the best tools available. Second, the performance of the discrete choice models is translated into an integrated energy-economy model (CIMS), so that the behavioral realism can be exploited within a broader modeling framework.

1.3 Focusing on Personal Urban Transportation

Many sectors in the Canadian economy present modeling challenges particularly well suited to a hybrid approach. Personal urban transportation, referring to the transportation needs of individuals within Canada's cities, is one of these well-suited sectors for two reasons. First, technology decisions for different vehicle and mode types are only partially driven by cost, where time, comfort, style, and reliability all play major roles in the decision making process. Because of these additional factors, simple least cost predictions will diverge significantly from reality. Second, the different technologies available are continually evolving, and are highly subject to policy influence so the historical experiences with transportation won't necessarily be repeated in the future. Various vehicle emissions standards show how much influence government can have over the energy efficiency and emissions of vehicles being sold in a region. Pilkington (1998) has examined the effect on technological innovation of major vehicle regulations in the United States such as California's Vehicle Emission Standard, and the more modest 1990 Federal Clean Air Act Amendments and the 1992 National Energy Policy Act. He concludes that although it is too early to tell if the CVES will succeed in its ambitious goals, all three pieces of legislation have helped spur the only major engine technology advancements in the last 15 years. These two characteristics of personal urban transportation necessitate a behaviorally realistic, and technologically detailed modeling approach. For these reasons, this research will take the technology choices for vehicle type and commuting mode as a framework for making CIMS a better hybrid model.

A more general justification for studying personal urban transportation is that the emissions are significant enough that policy will likely be aimed at reducing them, and as such, the capacity to effectively model the decisions within the sector will be beneficial. Although there are some countervailing factors, emissions have been increasing, with the primary factors being an increasing urban population, increasing popularity of larger vehicles, and a move towards single occupancy vehicles away from carpooling, transit, and non-motorized transportation (NRCAN, 2002). The combined result of these trends is that emissions from the sector are predicted to be 21% above 1990 levels by 2010 without any intervention, which is slightly less than the national average (Environment Canada, 2002). The federal government has recognized the significance of these trends, and the Climate Change Plan for Canada expects reductions of at least 21 megatonnes from personal urban transportation (Government of Canada, 2002). Clearly, policy intervention seems likely, and because of the complexity of the underlying technology decisions, a strong modeling approach will be beneficial.

There is a vast wealth of modeling experience in the transportation sector, and much of it will be used as the foundation for this research. Prior to the 1970's, the field was almost exclusively focused on aggregate forecasts of vehicle demand, but with the advent of tractable discrete choice modeling approaches, modelers took a much more technologically detailed approach (Manski, 1980). They developed models that focused on the intricacies of specific transportation related decisions such as the numbers, types, and vintages of vehicles that people prefer, and the types of modes they choose for work and recreational trips. This transition did not lead to a loss of behavioral realism because modelers continued to focus their understanding on the wide variety of factors that influenced transportation decisions. It did however necessitate a diminished focus on aggregate measures of demand because the new models were so detailed that a broad view of the economy was no longer feasible. The past twenty years has seen the underlying model specifications, and estimation routines advance considerably (McFadden, 2000), but much of the focus remains on the individual decisions that comprise the personal urban transportation system. Although these models have become increasingly sophisticated, they generally fail to see the larger pictures of how the different transportation decisions interact with one very notable exception being Hensher's (2002) work to develop an integrated urban passenger transport model system. This project combines a number of empirically estimated discrete and continuous choice models (vehicle type, number of vehicles, mode, time of commute, frequency of commute, and location of home for example) to comprehensively represent the transportation system in Perth, Australia.

The attempts of Hensher and others to tie together the disaggregated work in transportation decisions are undeniably valuable, but they fall short of a true hybrid approach from an energy-economy modeling perspective. The remaining problem is that these models still fail to relate how transportation decisions fit within the entire economy. Models like NEMS have attempted to integrate the models from discrete choice studies into their technology allocation algorithms, but these approaches have failed to include the wealth of decision-making factors contained in the original discrete choice models. Instead they have typically focused on the estimated relationships between operating and capital cost, because these attributes are already included in the model. This research will attempt to extend on the attempts of Hensher and NEMS, by including a network of transportation decisions within a larger energy-economy model, without losing the behavioral richness that defines the discrete choice models.

1.4 Structure

The remainder of the paper is divided into six chapters. Chapter two provides a more detailed description of discrete choice modeling in order to provide the reader with a solid foundation on the forthcoming modeling tools. With this understanding, it will become clear how discrete choice models are capable of providing greater behavioral realism to a model like CIMS. Chapter three summarizes the data collection process, and assesses the success of the different surveying steps. Chapter four focuses on the estimation and discussion of the discrete choice models, and presents the key results that are translated into CIMS in chapter five. CIMS' resulting improved behavioral capabilities are then demonstrated through some policy simulations in chapter six. Finally, chapter seven summarizes the results, and offers some key conclusions about the research.

2 Discrete Choice Models

Discrete choice models aim to understand and predict non-continuous choices, where consumers are forced to choose between a number of non-divisible goods or services. They focus on the choices of individual consumers, and attempt to extrapolate an understanding of the market demand from those individual preferences. As such, they are well-suited to anchor the behavioral realism axis of a hybrid energy-economy model. Based on the early work of McFadden (see McFadden, 1976 for an overview of this research), discrete choice models depart from the classical economic view of demand that sees choice alternatives as bundles of homogeneous and infinitely divisible goods. Instead, each good and service becomes defined by its unique attributes, which in turn influence a customer's attraction to it (Manski, 2001). Under this view, the attributes become the driving factors in consumer decision-making, and if they can be observed, the choices people make can theoretically be predicted. Attributes can range from measurable and tangible qualities such as price or weight, to highly intangible qualities such as attractiveness. In addition to the transportation applications that will be discussed, DCM's have been used, for example, to model residential decisions (Revelt and Train, 1997), choice of recreational activity (Schroeder and Louviere, 1999), and marketing applications (Verbeeke et al., 2000).

2.1 Random Utility Theory

In order to conceptualize a discrete choice model, assumptions need to be made about how consumers actually make decisions, or in other words, the modeler needs to guess what thought processes occur as a consumer finalizes on a choice. Understanding decision-making behavior is by no means a simple task; and Meyer and Kahn (1991) provide an overview of the more common theories of decision-making and how each can serve as the foundation for a modeling approach. Examples include feature elimination, and satisfycing, which both believe consumers have minimum acceptable thresholds for each feature or attribute. Feature elimination theorizes that consumers compare all alternatives simultaneously, one attribute at a time, and that they sequentially eliminate the alternatives that don't meet an attribute's threshold until a single choice remains. Satisfycing theorizes that consumers look at all of the attributes, one alternative at a time, until one is found that satisfies all of the thresholds. The two theories are very similar, but can predict different decisions when more than one alternative meets all of the minimum requirements. Distinct from these algorithms, utility maximization is the dominant choice theory in economics, and it is based on the proposition that consumers gain a measure of utility from any good or service they consume, and they will choose the goods and services that maximize their personal utility. In its most general form, the theory is attractive because it permits individuals to decide how important each attribute is in their decisions. This flexibility allows different decisions to be predicted for different people, even though they may face the same decision scenario. Utility maximization doesn't explain every decision, but it has remained a prominent piece of economic theory because intuitively it plays a part in many decisions, it is easily translated into a modeling framework, and it provides relatively robust predictions in many contexts.

Utility theory initially assumed that decisions could be completely understood based on the attributes in a choice scenario, resulting in deterministic predictions if all the attributes were known with certainty. Following this idea, utility was described by equation 2.1.

$$U_{ij} = V_{ij} \qquad \textit{(Equation 2.1)}$$

where U_{ij} is person i's utility for good or service j, and V_{ij} is person i's observed utility for good or service j. V_{ij} is commonly defined by equation 2.2.

$$V_{ij} = \vec{\beta}_{ij} \times \vec{X}_j + ASC_{ij} \qquad \textit{(Equation 2.2)}$$

where X_j is a vector of attribute values for good or service j, B_{ij} is a vector of person i's weighting coefficients for each of good or service j's attributes, and ASC_{ij} is an attribute independent (alternative specific) constant that person i associates with the utility of good or service j. A belief in this view of the world can be summarized by figure 2.1, which shows the probability that a certain amount of utility is gained from each of two competing technologies. According to this diagram, the probabilities for the two utilities are both 100%, so technology two will always have a higher utility, and will therefore always be chosen.

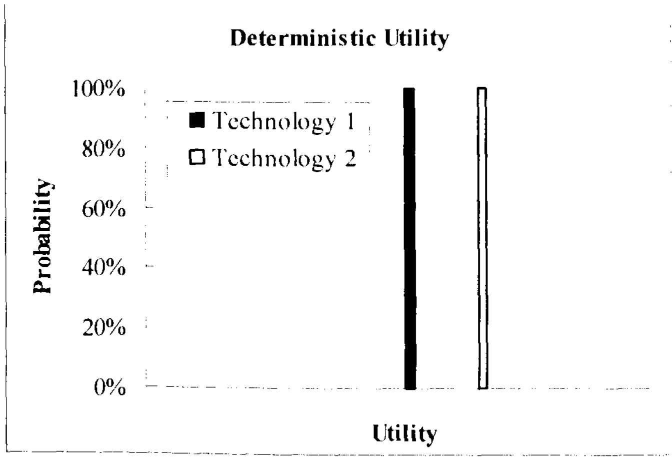

Figure 2.1 – Utility probability density functions in a deterministic world

Equations 2.1 and 2.2 suffer from the shortcoming that decision-making is too complex to be completely described with a simple set of observable parameters, and weighting coefficients. Train (1986) explains this inadequacy in two ways. First, some attributes that are important to a decision-maker won't be observable by an external researcher, and some aspects of the decision making process may even be unrealized or random to the decision-maker depending on the decision. Second, there will inevitably be some degree of measurement error when trying to assess what alternatives a person considers, and what attribute values they observe when making a choice.

The admission of these limitations led to the development of random utility theory, where utility is defined to contain an observable and unobservable (or random) component. This view of consumer decision-making leads to utility being defined by equation 2.3.

$$U_{ij} = V_{ij} + \varepsilon_{ij} \qquad \textit{(Equation 2.3)}$$

where U_{ij} is person i's utility for good or service j, and V_{ij} and ε_{ij} are the observable and random components of person i's utility for good or service j. V_{ij} is the same as described in equation 2.2, but only the key observable attributes are included as X_i's, with the less important or unobservable factors encapsulated within the error component.

Compared to the deterministic case in figure 2.1, the random component has the effect of converting U_{ij} into a distribution of possible outcomes instead of a single deterministic point. Figure 2.2 shows the likelihoods of different utility values for the same two technologies once an error term is included. Now, instead of technology two always being chosen, the overlap between the two curves indicates that each could possibly be chosen depending on the actual value of ε_{ij}.

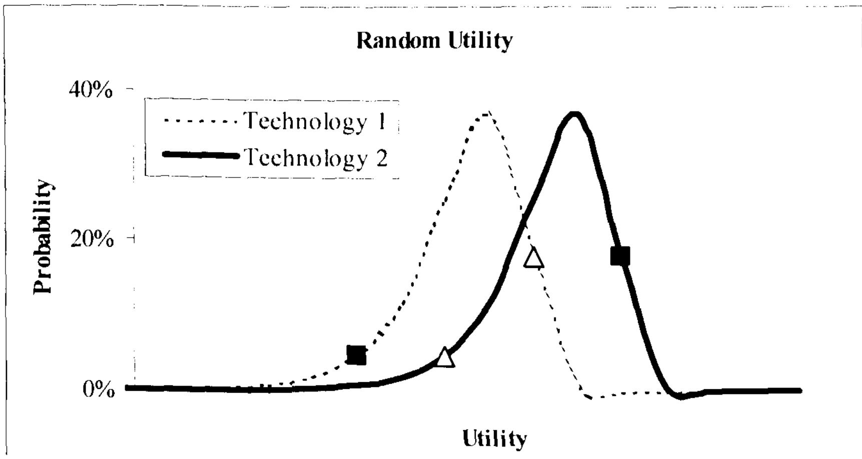

Figure 2.2 – Utility probability density functions in a stochastic world

If utilities were sampled from each of the two curves presented in figure 2.2 (the two dark squares for example), the point with the highest utility would be chosen (technology two). Each time this sampling process is repeated, the technology with the highest utility will be chosen, and as shown by the clear triangles, it is possible for technology one to be chosen even though it provides less utility on average. This stochastic nature leads to the probability that person A will choose technology one, $P_{A,1}$, being defined by equation 2.4.

$$P_{A,1} = P(U_{A,1} > U_{A,2}) = P(V_{A,1} - V_{A,2} > \varepsilon_{A,2} - \varepsilon_{A,1}) \quad \textit{(Equation 2.4)}$$

Both of the V terms are deterministic once the attribute values are known, so the probability that technology one will be chosen can be obtained by integrating over all possible values of the ε terms. Relating back to figure 2.2, the integration is analogous to sampling many pairs of points, and then calculating the proportion of pairs in which technology one provided more utility. If this information can be obtained for enough consumers, the average probability of a technology being chosen is equivalent to the new market share for that technology.

Although useful for explaining why consumer behavior can't be predicted with certainty, random utility theory in this form is not useful for modeling until assumptions are made about the V_{ij} and ε_{ij} terms. A researcher needs to decide what attributes will be included in the V_{ij} term, what mathematical form it will assume, what distribution describes the error term, and whether or not the error terms are correlated across the alternatives. Current work in discrete choice modeling is focused on hypothesizing, modeling and testing various formulations for the V_{ij} and ε_{ij} terms, but this research will use one of the earliest and most tested formulations; the multi-nomial logit model (Louviere et al., 2000).

2.2 The Multi-nomial Logit Model

The multi-nomial logit (MNL) model is a specific formulation of random utility theory, built on the assumption that the error terms, ε_{ij}, for each alternative are independently and identically distributed according to a type I extreme value distribution. Figure 2.3 shows the probability distribution function (pdf) of a type I extreme value distribution, which is defined by equation 2.5.

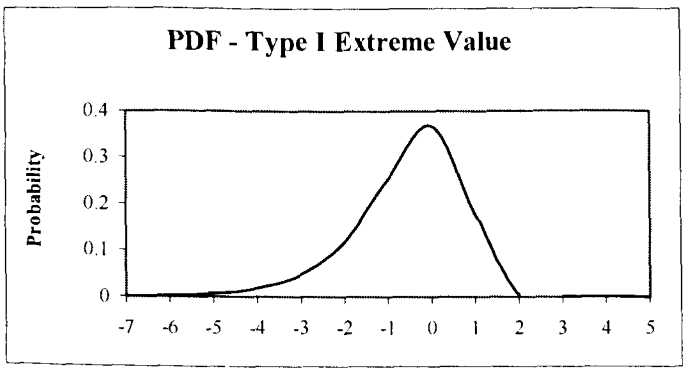

Figure 2.3 – Likelihood function for type I extreme value distribution

$$Likelihood(\varepsilon) = e^{\varepsilon} \cdot e^{(-e^{\varepsilon})} \qquad \textit{(Equation 2.5)}$$

When the choice probability function (equation 2.4) is integrated using identical and independent extreme value distributions for the error terms, equation 2.6 results[5].

$$MS_i = \frac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}} \qquad \textit{(Equation 2.6)}$$

Although this equation is derived from expressions that contain the random error terms, the market shares are simply functions of the β_i's and X_i's that make up each V_i. This closed form, analytical solution means that the exact values of the unobserved components of utility are not needed to estimate the model or calculate market shares.

The choice of this error distribution in the MNL model implies that the unobserved component of utility is most likely to be zero, but the distribution is skewed to the left. Also, the error terms are independent of each other, so a certain error for one alternative does not influence the likelihood of the other error terms. Realistically, these assumptions about shape and correlation of the error terms are probably never completely satisfied, but in practice many decisions come close. The significant advantage presented by these assumptions is that the integration of equation 2.4 results in a closed form equation to calculate market share, whereas the probability distribution functions of other, possibly correlated distributions result in much more complex equations. When these models were first applied by McFadden, the computer power needed for numerical approximations, or simulation based approaches was not available, so the simple analytic solution presented by assuming extreme value type I distributions for the errors was very attractive (McFadden, 2000).

The assumed independence of the error term results in the relative choice probabilities between any two choices being independent of all the other choices (even if new alternatives are added to the choice set). This implication is known as the independence

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[5] The utility equations in the MNL model no longer contain a subscript for individual consumers. Model flexibility isn't reduced because personal characteristics such as income or education can be interacted in the utility function to produce individuality, or models can be segmented into relatively homogenous groups to test for different attribute weighting coefficients.

from irrelevant alternatives (IIA), and it is often cited as a significant shortcoming of the MNL model. It means that if a MNL model predicts market shares of technology one and two to be 50% each, their relative proportions will remain constant as long as their attributes aren't changed. Even if a third option is added that gains 30% market share, the original two technologies will still earn equivalent market share, or 35% each. Similarly, if one technology's attributes values are changed so that it gains more market share, all other technologies lose market share proportionally, so that their relative shares remain constant. The potential problem associated with the assumption of independent error terms is commonly illustrated using the red bus, blue bus paradox. In the paradox, a car and the red bus each initially get 50% of the market share, and after a second blue bus is introduced, instead of each bus receiving 25% market share, all three alternatives receive 33% because the red bus and car need to maintain their relative probabilities. The validity of the IIA assumption is obviously an important concern, but the associated problems can generally be avoided if the alternatives are chosen appropriately.

Discrete choice modelers are well aware of the problems presented by the assumptions of the MNL model, and much of the field's current research is focused on new formulations, and finding ways to relax assumptions, while still producing tractable models. Train (2003) and Louviere (2000) both provide excellent overviews of some of these alternate approaches. Despite the limitations of the MNL however, it continues to be the most dominant formulation used by discrete choice modelers, and so long as the assumptions are not drastically violated by the choice situations or predictive requirements of the model, the models continue to provide valuable information (Louviere, 2000). These reasons, in combination with the wealth of literature on MNL models and the relative accessibility of the mathematics justify the use of the models in this research.

2.3 Data Requirements

Discrete choice models for a given decision are estimated using information about the choices available in that decision (the attributes and their levels), and the choice made. The attributes can include whatever the modeler chooses as long as they can be observed in some way each time the choice is made. The choice can be made numerous times by the same or different people, and even if the attribute levels remain constant, the models can accommodate different choices because of the unobserved component of utility. Once all of the data is collected, β parameters are estimated to provide the most likely explanation of consumer behavior given the choices that were made.

The observed choices can be from real market data (revealed preferences), or from hypothetical situations (stated preferences). The advantage of revealed preferences is that they reflect the actual behavior of consumers, whereas with stated preferences, people's actions don't always reflect their stated intentions. This significant advantage is restricted by three distinct problems. First, technology attributes in real world data are often correlated (it is often hard to disassociate price from quality for example) making it difficult to isolate the importance of each attribute. Second, the alternatives a customer was choosing between, and the attribute levels they observed when making the choice are often difficult to obtain (especially for the alternatives not chosen). Third, it is often desirable to understand how people will react to technologies that have significantly different attribute values from those currently observed, or for technologies that aren't even available yet. In these cases, it is impossible to obtain revealed preference information because the tradeoffs are fictional. Stated preference data doesn't suffer from any of these drawbacks, as the technologies and attribute levels can be set to allow a full range of tradeoffs to be observed. Of course, if a technology is too different from what is currently available, people will have difficulty accurately saying whether or not they would select it.

Revealed and stated data are not mutually exclusive, and it can be advantageous to combine both sources to estimate models, because the strengths of the two data sources are natural complements to one another (see Brownstone et al., 2000 for an example). Due to time constraints, and the additional complexities involved in combining separate data sources, only one type of data could be used, so in the case of this research the models were based on stated preference data. This choice was made because both choice experiments test scenarios designed to reflect different policy initiatives, which aren't currently observed across Canada. Examples of this include higher gasoline taxes, levies on polluting vehicles, and express access for carpools and transit. Also, the hydrogen fuel cell car, which is not yet commercially available, was tested as an alternative in the vehicle choice experiment. It should be noted that some of these policies have been tried in specific regions or municipalities, but trying to piece the revealed responses together and sort out the underlying factors would have been too problematic for this project. Instead, choice experiments were developed for both mode and vehicle choice and the stated preference data was collected using a mail survey, which is described in the following section.

3 Choice Experiment Methodology

The choice data needed to develop the discrete choice models was collected by first recruiting potential participants at random by telephone, and then mailing a survey containing the choice experiments to those who agreed to participate. This approach allowed the sample population to be screened for certain criteria, and queried for personal information that would be used to customize the mailout survey. These features are advantageous because the screening allows the survey to be targeted to a specific population, and the customization helps make the questions less hypothetical, and more meaningful to individual respondents. As a result, response rates are generally higher than simple mailout surveys, and the results are probably more reflective of respondents' views (Dillman, 1999). This section discusses the choice experiment design (section 3.1), the telephone recruitment process (section 3.2), and the mailout process (section 3.3). The mailout survey was designed between mid August 2002, and late September 2002 in order to be ready for the telephone recruitment, which commenced on October 7, 2002. The recruitment and subsequent mailout processes lasted for three weeks, after which surveys were collected until January 2003.

3.1 Choice Experiment Design

The finalized mailout survey consisted of five parts looking at transportation options and habits, vehicle preferences, commuting mode preferences, views on transportation issues, and additional demographic information. The survey contained a total of 48, mostly multiple-choice questions, and took up four double-sided legal-sized sheets of paper, with completion time estimated to be around twenty-five minutes. Appendix 2 contains a sample copy of the survey instrument. For the purposes of this research project, the discrete choice experiments contained in the vehicle and mode preference sections (question 21 to 24 and 26 to 29) are the key components of the survey instrument. These experiments asked respondents to make hypothetical decisions between different vehicles and modes based on various attribute levels so that the importance of each attribute could be assessed. The questions in the other parts of the survey were designed to fill in gaps that were anticipated from the choice experiment, help provide explanatory variables for respondent choices, and improve the flow of the survey so that it was easier to understand and complete.

3.1.1 The Vehicle Choice Experiment

Each survey contained four hypothetical vehicle choices, asking the respondent to choose between a standard gasoline vehicle, an alternative fuel vehicle, a hybrid-electric vehicle, and a hydrogen fuel cell vehicle. These four vehicle types were selected because they represent a full spectrum of engine technologies currently available, and likely to be available in the foreseeable future, and they fit well with the options currently modeled in CIMS. Respondents were informed that each vehicle was like the type they currently drove (this information was collected in the telephone survey), but beyond the attributes contained in the choice experiment, no additional information about the vehicle was provided. The survey did not contain an option for someone to say they wouldn't choose any of the given vehicles for two reasons. First, choosing no vehicle was not a realistic option because they were assumed to be replacing their current vehicle. Second, the costs and variables presented in the survey often represented policy scenarios, so a person's current expectations for the values of key attributes wouldn't necessarily be valid anymore.

A detailed literature review was undertaken to select the attributes that were used to describe each vehicle. Looking for attributes that were consistently significant, and could be influenced through policy, the resulting six attributes were the purchase price, the fuel costs, the percentage of stations selling the proper fuel, whether or not the vehicle would be granted express lane access, the emissions compared to a standard gasoline vehicle, and the power compared to their current vehicle. Table 3.1 summarizes some of the other studies that have used these attributes in discrete choice models for vehicle choice.

	Attribute					
Article	Capital Cost	Operating Cost[6]	Fuel Available	Express Lane Access	Emissions Data	Power[7]
Ewing, 2000	✓	✓		✓	✓	✓
Bunch, 1993	✓	✓	✓		✓	✓
Greene, 1988	✓		✓			
Brownstone, 2000	✓	✓	✓		✓	✓
McCarthy, 1998	✓	✓				
Manski, 1980	✓	✓				✓
This study	✓	✓	✓	✓	✓	✓

Table 3.1 – Other vehicle choice models that have used similar attributes

This list of six attributes certainly isn't exhaustive, but unfortunately everything couldn't be included in this study. Some of the most notable exclusions that have been used in the studies mentioned in table 3.1 include the makes and models available, safety, reliability, seating and storage capacity, driving range, and refueling time. The last five were not included because although they have been found to be important attributes it was assumed that all four vehicle types could achieve comparable performance on these factors. Make and model availability, safety, and reliability, will likely vary in the eyes of consumers for the different vehicle types, but they were not included in the choice experiment because the size of the experimental design was limited in the number of attributes explored, and these attributes were either too complicated to account for, or they were considered less important than those already included. Although they weren't explicitly part of the choice experiment, most of the excluded attributes were indirectly measured in question six of the survey, which asked respondents to rank the importance of various vehicle attributes on a one to five scale. The use of these results in combination with the choice experiment results is discussed in section 4.2.1. Also not included in the choice experiment are the personal characteristics, which can influence an individual's decisions. Demographic information on gender, age, income, family size, education, and occupation was collected in the survey, and its use is discussed in section 4.3 regarding the estimation of models using segmented samples.

[6] Includes both maintenance and fuel costs.

[7] Includes attributes like performance, top speed, and acceleration.

Table 3.2 shows the possible levels that each of these attributes could take independently in each survey. For example, four different values were possible for the purchase price of the gasoline vehicle, while only two were possible for the other types of vehicles. In total, two attributes could assume four values independently of the other attributes, and twelve attributes could assume two values independently of the other values. Two attributes (italicized in table 3.2) were set according to a separate value in the design in order to allow their levels to vary without using up a degree of freedom. These were the fuel cost of the hybrid electric vehicle (equal to 75% of the gasoline vehicle's fuel cost), and the hybrid electric vehicle's access to express lanes (equal to the alternative fuel vehicle's access). For example, if the fuel cost for gasoline assumed the value 110%*N_{CC}, the hybrid electric vehicle would cost 75%*110%*N_{CC}. The remaining eight attributes were constants. This formulation resulted in a 2^{16} full factorial design (each four level attribute was treated as 2^2), for which a resolution IV, 2^{16-11} fractional factorial design was used to conduct the choice experiment (see section 3.1.3).

Vehicle Type	**Gasoline Vehicle**	**Alternative Fuel Vehicle**	**Hybrid-Electric Vehicle**	**Hydrogen Fuel Cell Vehicle**
Purchase Price	•100% N_{CC} •105% N_{CC} • 110% N_{CC} •115% N_{CC}	•105% N_{CC} •110% N_{CC}	• 105% N_{CC} •120% N_{CC}	•110% N_{CC} • 120% N_{CC}
Fuel Cost	•100% N_{FC} •110% N_{FC} • 120% N_{FC} •130% N_{FC}	•110% N_{FC} •120% N_{FC}	•*Equals 75% Gasoline Value*	•110% N_{FC} •120% N_{FC}
Stations with Proper Fuel	•100%	• 25% •75%	•100%	•25% •75%
Express Lane Access	•No	• No •Yes	•*Equals AFV Value*	• No •Yes
Emissions Compared to Current Vehicle	•Equal	•10% Less	•25% Less	•100% Less
Power Compared to Current Vehicle	•Equal	•Equal •10% Less	•Equal •10% Less	•Equal •10% Less

Table 3.2 – Possible attribute values in vehicle choice experiment

The purchase price and fuel costs of the four vehicles were based on the respondent's current expenses, with N_{CC}, and N_{FC} referring to values obtained in the telephone survey[8]. The variations around those base values were selected from current market data, and information in the CIMS database. On average, gasoline vehicles had the cheapest capital costs followed by alternative fuel vehicles, hybrid electric vehicles, and hydrogen fuel cell vehicles, but any ordering was possible depending on the choice profile. Hybrid electrics had the cheapest fuel costs regardless of the profile, while the remaining three vehicles types had the same average cost, which, depending on the choice profile could be ranked in any order. Of particular note are the prices for the hydrogen fuel cell vehicle, which are well below any anticipated initial market price (set at 10 or 20 percent above current gasoline vehicle prices). The reason for this discrepancy is that differences in capital costs exceeding twenty percent have been found to dominate vehicle choice decisions (Ewing, 2000 and Washbrook, 2002), so if more realistic prices had been used, the hydrogen fuel cell vehicle would never have been chosen. If an alternative is selected too few times, the tradeoff points at which it becomes preferred can't be estimated, and the alternative can't be included in the model. The remaining attributes levels were chosen based on the values found to be significant in other studies, with the most notable being the percentage of stations with proper fuel. The minimum value of 25% was selected because Greene (1988) found that as availability dropped under 25%, utility quickly decreased non-linearly. Although it would have been interesting to observe these effects as well, the limits of the design prevented this given the large number of other attributes being examined.

3.1.2 The Mode Choice Experiment

Similarly to the vehicle choice experiment, each survey contained four questions asking the respondent to choose between five modes for their commute to work. The options provided were driving alone, carpooling, taking public transit, using a park and ride service, and walking or cycling. Additional modes are obviously available (a more

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[8] If the respondent either didn't know the capital and fuel costs of their current vehicle, or didn't have access to a vehicle, the sample averages for N_{CC}($20,000), and F_{CC} ($125/month) were used.

detailed breakdown of public transit for example), but the size of the experimental design and the available space on the survey page limited the number that could be included. The five that ended up being chosen were selected because they were either the most heavily used, or they were available to the greatest number of potential new users. Space limitations on each survey page made it impossible to fit all five choices on a page, so if the respondent lived up to fifteen kilometers from work they were given the walking/cycling choice, or if they lived further away than fifteen kilometers they were given the park and ride option. This step did not impose an assumption that the respondent would not have selected the excluded choice if they had been given the option because the eliminated choices were accounted for during model estimation (see section 4.2.1). As with the vehicle choice experiment, respondents were not given the option to choose none of the choices because it was assumed that they would need to continue commuting to work, and that the choices they are currently making might not be available because of policy influences. It should be stressed that this choice experiment focused solely on mode choice decisions for commuting trips, and that other types of trips such as shopping, recreation, and social visits often have considerably different attributes and decision criterion.

Unlike the vehicle choice experiment, the attributes describing each option in the mode choice were not identical. Driving alone was described with the total travel time, and cost; carpooling was described with traveling time, pickup/drop off time, and cost; public transit and park and ride were described with traveling time, walking/waiting time, cost, and the number of transfers; and walking and cycling was described using the traveling time, and whether or not a bike route was present. These attributes were all selected based on a review of existing research (table 3.3 shows other studies that used these attributes), and pre-survey discussions. As with the vehicle choice experiment, the attributes presented in the survey were not exhaustive, but additional options were not considered to be as important, and their inclusion would have overextended the experimental design, and overcomplicated the survey presentation for respondents. Some of the excluded attributes that were discussed in the other surveys mentioned in table 3.3 were environmental impact, reliability, traveling speed, privacy, and level of congestion.

Time and costs have also been more finely divided than in this study, so that the importance of waiting versus walking time could be differentiated for example. Reliability in particular, has been cited in some studies as a key deterrent stopping people from using modes other than single occupancy vehicles (Translink, 2003), and the decision to exclude it as a factor instead of the number of transfers was relatively arbitrary. Despite the fact that these attributes were not included in the experimental design, they were examined separately in question 13 of the survey, and a discussion of how these results fit with the estimated models is presented in section 4.2.2.

	Attribute					
Article	Travel Time	Cost	Pickup Drop-off Time	Walking / Waiting Time	Number of Transfers	Bike Route Access[9]
Train, 1979	✓	✓		✓	✓	
Washbrook, 2002	✓	✓	✓	✓		
Asenio, 2002	✓	✓	✓	✓	✓	
Palma, 2000	✓	✓				
Bhat, 1997	✓	✓		✓		
This study	✓	✓	✓	✓	✓	✓

Table 3.3 – Other mode choice models that have used similar attributes

Table 3.4 describes the possible levels for each of these attributes, where all attributes could independently take on two values except for the SOV travel time that had four possible levels. N_{Time}, N_{Cost}, and N_{Dist} refer to the traveling times, commuting costs, and distances that each respondent provided in the telephone survey, each of which were used as reference points for the attribute levels[10]. The possible values presented in table 3.4 indicate fifteen two-level attributes, and one four-level attribute, resulting in a 2^{16} full factorial design, which as in the vehicle choice design was implemented using a resolution IV, 2^{16-11} fractional design (see section 3.1.3). The different levels were selected to reflect the real differences between different modes, scaled to the respondent's current situation, which helped produce a range of values reflective of the diversity experienced across the country. The range of values explored for travel time allowed for

[9] No discrete choice models for mode choice reviewed in the literature contained a cycling option.
[10] For the respondents who didn't commute, sample averages for N_{Time} (25 minutes), and N_{Cost} ($125/month) were used in the choice questions. For the respondents who didn't commute by SOV, N_{Time}, and N_{Cost} were calculated using the inverse of the formulas for non-SOV driving times in table 3.4.

any of the five modes to be the fastest in a given choice set, but on average driving alone was the fastest available mode, followed by carpooling, park and ride, and public transit. The ranking for walking and cycling depended on the value provided for N_{Dist}. For costs, carpooling was always cheaper than driving alone, and transit was always cheaper than park and ride. The relative magnitudes of these two groups depended on the value provided for N_{Cost}.

Vehicle: Alone	Vehicle: Carpool	Public Transit	Park and Ride	Walk or Cycle
Travel Time • 90% N_{Time} • 100% N_{Time} • 110% N_{Time} • 120% N_{Time}	*Driving Time* • 90% N_{Time} • 100% N_{Time}	*Driving Time* • 105% N_{Time} • 115% N_{Time}	*Driving Time* • 95% N_{Time} • 105% N_{Time}	*Travel Time* • N_{Dist} ÷ 6km/hr or N_{Dist} ÷ 15km/hr • N_{Dist} ÷ 8km/hr or N_{Dist} ÷ 20km/hr
	Pickup/Drop-off • 5 minutes • 10 minutes	*Walk/Wait Time* • 5 minutes • 15 minutes	*Walk/Wait Time* • 5 minutes • 10 minutes	
Cost • 100% N_{Cost} • 110% N_{Cost}	*Cost* • 50% N_{Cost} • 75% N_{Cost}	*Cost* • \$60 / month • \$100 / month	*Cost* • 25% N_{Cost} + Transit Value • 50% N_{Cost} + Transit Value	*Cost* • \$0 / month
		Transfers Needed • None • One	*Transfers Needed* • None • One	*Bike Path Available* • Yes • No

Table 3.4 – Possible attribute values in mode choice experiment

3.1.3 Experimental Design

The previous two sections have mentioned that both the vehicle and mode choice experiments were carried out using resolution IV, 2^{16-11} designs. The experimental design dictates the combinations of attribute levels that will be explored in the choice experiment. Efficient experimental designs eliminate the need to test all possible attribute level combinations, while ensuring that the effect of each attribute can still be estimated independently. A design is referred to as orthogonal when it ensures that none of the attributes of interest are collinear across the choice sets. The 2^{16-11} design used in this study is a resolution IV design[11], which is important because using a resolution IV design ensures that the effect of each attribute can be estimated independently from the influence of other attributes or combinations of attributes (Montgomery, 2001). If a lesser resolution was used, the importance of each variable could not be separated from the influence of the other variables, and useful predictions would be impossible.

The 2^{16-11} design results in thirty-two different profiles (or choices) that can each be converted into a mode or vehicle choice question (i.e. the attribute levels for four vehicles or five modes). The complete design is contained in appendix 3. In order to create blocks of four questions for each survey, these profiles were first randomized, and then arranged into sets of four profiles two different ways. This process resulted in the sixteen sets of choice profiles (available in appendix 3), where each choice profile appears twice (although never in combination with another profile more than once). These sets were assigned to respondents as they were recruited ensuring that the sets were distributed evenly across each of the eighteen cities to minimize the possibility that any single set of choices would be over or under represented in a specific city. For example, when the first batch of surveys was printed, if there were seven respondents from Calgary, choice sets one to seven would be assigned to those respondents. When the next batch of surveys was printed, the next Calgary respondent was given choice set number eight.

Although this process succeeded in achieving an even distribution of choice sets at the city level, it unintentionally introduced a slight bias at the regional and national levels. The assignment of choice sets for each city was always initiated with choice set number one, so the higher number choice sets had a higher probability of being underrepresented by a single choice set in each city. For example, if a city had thirty respondents, choice sets fifteen and sixteen would only be assigned once for that city, whereas all the other choice sets would be assigned twice. The influence of this bias was reduced because the choice profiles were ordered two different ways, so even though choice set 16 was

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[11] The 2^{16-11} design was obtained by making a copy of the resolution III, 2^{15-11} design described in Montgomery (2001), then reversing all of the copied version's signs, and combining it with the original. The 16^{th} factor is created from the original identity element, which is the product of all of the factor levels. Performing these steps on any resolution III design results in a resolution IV design (Montgomery, 2001).

underrepresented, profile numbers 19, 14, 10, and 15 also appeared in one other choice set. With the bias being replicated in all 18 cities, the least distributed profile (number 15) was distributed 18 times fewer (12%) than the most distributed profile (number 4). A complete listing of distribution frequencies for each profile is available in appendix 3.

Once the sets of profiles were assigned to each respondent, the generic design levels were replaced with the mode and vehicle choice attribute levels described in tables 3.2 and 3.4. This process allowed each choice question to be customized to the individual based on the capital cost of their current vehicle (N_{CC}), their average fuel costs (N_{FC}), their normal commuting time (N_{Time}), and their expected walking and cycling time based on their commuting distance (N_{Dist}). The fuel costs were also presented in weekly or monthly units depending on which the respondent preferred, and the respondent's car type was included in the descriptive information about the vehicle choice. All of these steps in combination helped personalize each survey so that the choices were as realistic as possible, hopefully facilitating more realistic responses.

As mentioned, the design used for both the mode and vehicle choices facilitated an independent estimation of all the main effects, and in both experiments a wide range of alternatives and attributes were tested. The design faces a number of specific limitations however, most notably in the number of attribute levels being explored. Most attributes were only set to two possible levels, which limited model predictions to linear relationships. Specifically, when only two levels are explored, it becomes impossible to identify increasing or decreasing marginal utilities or upper and lower threshold for attributes. Knowing this, the developed models should be used with caution in scenarios where the attribute levels differ significantly from those explored in the choice experiment. This limitation will have the most impact on the costs of hydrogen fuel cell vehicles (and to a lesser degree hybrid-electric cars), which were set at prices much lower than would be expected without significant subsidies. A second limitation was that the design was fully saturated, which means that reducing the number of attribute combinations (choice profiles) any further would have reduced the design's resolution. Although the design used was still resolution IV and orthogonal, it only explores 32 attribute combinations compared to the 65,536 that are available in the full 2^{16} factorial design, so 65,502 attribute combinations were not explored. More attribute levels or a larger fractional design were not used because the number of alternatives and attributes being explored had already dictated a large design, and a larger design would have given an unacceptably low probability of obtaining the necessary number of responses for each profile. If for example, the design had included 64 profiles, and the sample size had remained unchanged, each profile would have been sent to half as many respondents.

3.2 Telephone Recruiting

CGT Research International was contracted to recruit 1,150 participants for the mailout survey. The sample was drawn at random from Canadian households living in urban centers with populations over 250,000, and respondents were recruited between the 5th and 16th of September, 2002. Smaller cities weren't sampled because the availability of transportation alternatives is limited, and the choices being explored in the mode choice experiment wouldn't have been meaningful. The respondents were stratified according to regional, and then metropolitan area population, resulting in the sampling frame summarized in table 3.5 based on Canadian census data (Statistics Canada, 2001). This stratification process yielded city sample sizes that weren't proportional to city populations in other regions, but it ensured that smaller cities received enough responses to accurately represent each population. For example, if the stratification was based purely on city size, Halifax would have accounted for 1.7 percent of the sample, instead of the 5.3 percent achieved using the method described above. All of the deviations between the desired and actual sample size were acceptable.

Region	City	Population	Sample Size		Diff.
			Desired	Actual	
British Columbia	Vancouver	1,829,854	131	130	1
	Victoria	288,346	21	21	0
Prairie Provinces	Calgary	879,277	69	69	0
	Edmonton	782,101	61	66	-5
	Winnipeg	626,685	49	48	1
	Saskatoon	196,816	15	16	-1
Ontario	Toronto	4,366,508	262	257	5
	Ottawa – Hull	827,854	50	58	-8
	Hamilton	618,820	37	36	1
	Kitchener	387,319	23	23	0
	London	337,318	20	24	-4
	St. Catharines – Niagara	299,935	18	21	-3
	Windsor	263,204	16	17	-1
	Oshawa	234,779	14	17	-3
Quebec	Montréal	3,215,665	230	216	14
	Québec	635,184	45	43	2
Atlantic Provinces	Halifax	276,221	61	62	-1
	St. John's[12]	122,709	27	30	-3

Table 3.5 – Desired and actual sample stratification

Before accepting any individual respondent, the telephone recruiters were instructed to test the following filters. First, to comply with Simon Fraser University ethical guidelines, anyone younger than 19 was not permitted to participate (SFU, 2001). Second, each respondent needed to either have access to a vehicle, or commute to work or school at least once per week. Although people not meeting these criteria still have important transportation related concerns, it was decided that their responses to the mode choice and vehicle choice questions would be unreliable, and that they would present too broad a population to administer a concise survey instrument to. In total, of the 1,266 people willing to participate in the phone survey, 55 were filtered out because of no access to vehicles and no commuting, and 57 were eliminated because they were too young or not available during the survey period. The complete script of phone interview questions is available in appendix 2.

In addition to the filters purposely applied, certain subsets of the population could have been unintentionally over or under-represented depending on how available they were.

In order to maximize the probability of contacting each sampled household, surveying was conducted between noon and 10:00 pm in each time zone, and each household was called up to fifteen times before a replacement was sampled. Despite these efforts, certain populations will inevitably be more available to take phone calls, and because filtering on a number of demographic factors would have been prohibitively expensive, the potential for coverage biases could not be eliminated. To find these biases where they did occur, demographic information from the survey was compared with the 1996 and 2001 Canadian Censuses, where large differences between the two populations would indicate that a coverage error had occurred for some reason. Unfortunately, the ranges used to collect demographics in the survey did not match exactly with Statistics Canada data, so the statistical significance of any biases cannot be tested here. The largest bias was the overrepresentation of retirees, and homemakers, which can be explained by the fact that these two groups are much more likely to be available for phone calls at home. Apart from this, the remaining biases appear to be relatively minor, where compared to the Canadian averages, the sampled population has a higher family income, a higher proportion of females, a higher level of education, a larger family size, and is slightly older.

A related problem, which is one of the significant weaknesses of telephone recruitment surveys, is the potential for self-selection biases. This problem can occur because respondents are able to decide whether or not to participate once they had been contacted, and if the people who chose not to participate possessed characteristics or attitudes not present in the participating population, the results would be biased. Detecting a self-selection bias is impossible in this study because nothing is known about the people who choose not to participate, but the potential for this bias is illustrated in figure 3.1, which shows the breakdown of all valid telephone numbers that CGT International attempted to contact. Combining the groups where no was contact made, and those that refused to participate yields almost 85% of the total sampling frame, indicating a significant

[12] With a population of only 122,709 (Statistics Canada, 2001), St. John's, NF was also included to provide an additional center in Atlantic Canada.

potential for a bias to exist within either group. Unfortunately there is no way around this potential problem, and it is a standard concern with survey research based on telephone recruitment.

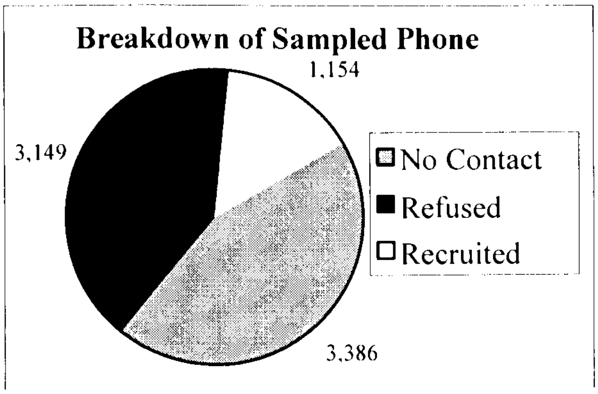

Figure 3.1 - Potential for self-selection bias

3.3 Mailout survey

3.3.1 Conducting the Survey

The mailout survey consisted of up to three separate contacts to ensure each participant had ample time and opportunity to complete the questionnaire. Throughout the survey process, all respondents were kept aware of the fact that their participation was voluntary, and that they could withdraw at any time. The researcher's phone number and email address were provided so that any questions could be posed, and respondents were also provided with a contact number for the School of Resource and Environmental Management's director in case they had concerns about the survey that they might not feel comfortable discussing with the researcher. All correspondence was carried out in English or French, depending on the respondent's preference.

The first mail contact occurred immediately following the recruitment between October 10, 2002, and October 20, 2002, with each participant being sent an initial copy of their survey. Because the phone recruiting took place over 11 days, surveys and accompanying cover letters (see appendix 2) were mailed in batches so that the delay between recruitment and mailing would be minimized. The mailout dates, and average delay from recruitment date are summarized in table 3.6, with the maximum delay of eight days occurring because of a reporting problem from the recruiting firm[13]. Each package included a loonie as a thank you for taking the time to participate, and a promise to donate an additional loonie to Unicef for each survey returned. A stamped and addressed return envelope was also included in order to minimize the respondent's time and cost commitments. These types of financial enticements have been found to significantly enhance survey response rates (Dillman, 1999).

Mailout Date	Surveys Mailed	Average Delay From Initial Contact (Days)
October 10, 2002	315	3.00
October 13, 2002	597	5.13
October 15, 2002	70	3.07
October 20, 2002	172	4.42

Table 3.6 – Average delay from phone contact for each batch of survey mailings

Two weeks after the initial mailout, each respondent who hadn't already replied (770 in total) was sent a follow-up postcard (see appendix 2) to remind them to complete the survey, or thank them if the survey had been sent back, but not received. This phase of the mailout process resulted in two noticeable benefits. First, the postcards were delivered to three respondents who never received the initial mailout for some reason[14], so they were provided with replacement packages. Second, and most importantly, the reminder seems to have had a positive effect on response rates as shown in figure 3.2. Responses were highest in the second week after the initial mailing, after which they fell by 55 percent in week three. In week four however (two weeks after the postcards were mailed), the response rate stabilized for one week, which could be the result of the postcards. Although not conclusive (the response rate did still fall slightly), this finding corresponds with existing survey research that finds early follow-up contacts to be effective tools to elicit additional responses (Dillman, 1999). In total, the follow-up postcards look to have increased responses by upwards of 100 surveys making them a worthwhile component of the data collection process.

[13] These twelve respondents were contacted again by phone to explain the delay in their survey.

[14] A total of 28 surveys were returned due to incorrect or incomplete addresses, and attempts were made to contact each of these respondents. Of these mistakes, 12 were corrected and sent a replacement package, while the remaining 16 either had intentionally provided an incorrect address, or could not be contacted.

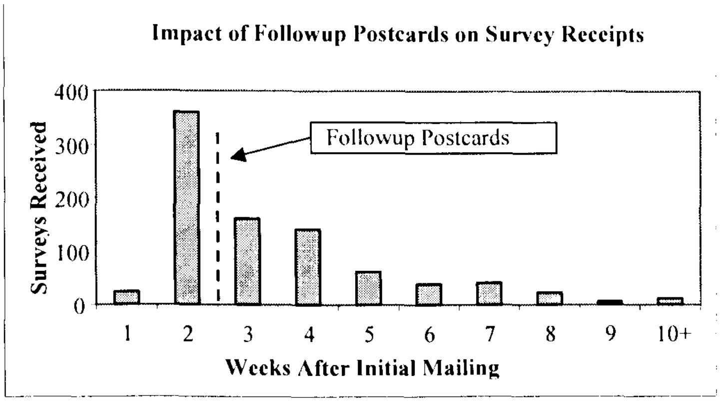

Figure 3.2 – Surveys received by the number of weeks after the initial mailing

As a final contact, the 386 remaining respondents who had not returned their surveys by November 18, 2002 were mailed an identical replacement survey with a revised cover letter (see appendix 2) explaining that the survey was drawing to a close, and that their responses were still important to the project. Figure 3.3 illustrates the impact of the follow-up mailout on weekly response rates, and as with the follow-up postcard, the replacement survey appears to have had a minor effect shown by the small increase in returns two weeks after the final package had been mailed. Unlike the postcard however, the increase is much smaller (up to 15 surveys), and it is questionable as to whether or not the cost was justified.

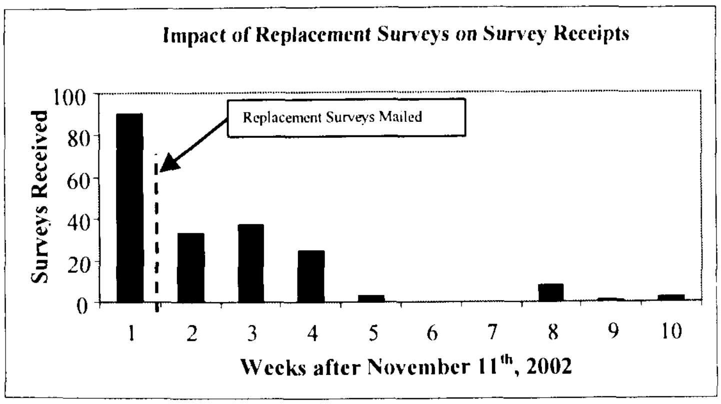

Figure 3.3 – Surveys received by the number of weeks after November 11, 2002

3.3.2 Response Rate

Surveys were collected until January 31, 2003; at which point 878 of the initial 1154 had been returned resulting in a raw response rate of 76%. To obtain a more accurate calculation for response rate, incorrect addresses (24), blank surveys (10), and surveys that weren't taken seriously (2) were removed, resulting in a data set of 866 surveys out of a potential 1118, or a revised response rate of 77%. This response rate of 77% compares well with Dillman's (1978) expectation of 81% for combined telephone-mailout surveys to a general population. In his more recent work, Dillman (1999) explains that expectations today should be lower for telephone based work because of the dramatic increase in telemarketing, and the introduction of call screening and call answer technologies. The observed response rate also compares well with similar transportation choice studies that used similar methodologies involving phone recruitment followed by mailout surveys. Some examples include Brownstone (2000) with 66%, Ewing (2000) with 59%, and Washbrook (2002) with 84%. An additional point is that these types of studies commonly focus on specific localized populations, which is expected to increase response rates by ten percent (Dillman, 1999), whereas this research questioned a much broader population base. Based on this information, the 77% response rate achieved in this survey is extremely satisfactory, and it can be concluded that the multiple personalized contacts overcame any drawbacks associated with targeting the survey to the general population.

3.3.3 Response Bias

Although the response rate was high, 23% of the recruited population did not return a completed survey, and if common characteristics or attitudes were present within this 23% that weren't represented in the returned surveys, the results would be subject to a response bias. Unlike the self-selection bias, limited information is available on the recruits who did not return surveys (because they completed the telephone survey), so it is possible to see if any differences exist between them and the rest of the population. Figures 3.4 through 3.8 contrast the demographics for the respondents that returned the survey with those that did not. If any of these breakdowns were significantly different, it would indicate that the survey appealed to a certain portion of society more than another, so that their response rates didn't match with their recruitment rates. The figures show that the available demographics are relatively unchanged between the populations who returned and didn't return the surveys, so based on the limited statistics available, no response biases are present.

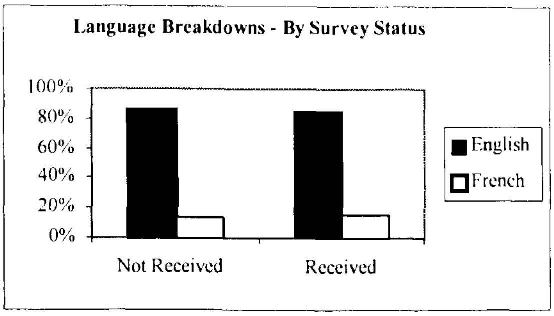

Figure 3.4 – Response bias in language

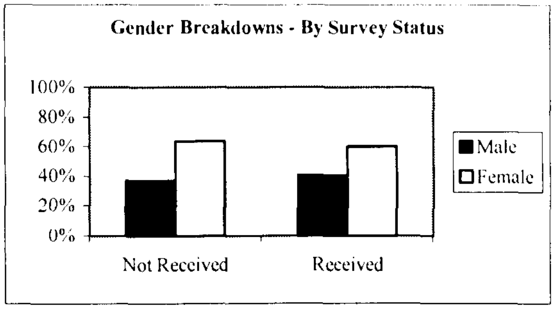

Figure 3.5 – Response bias in gender

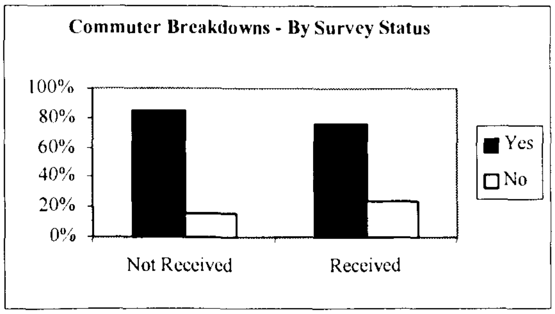

Figure 3.6 – Response bias in commuters

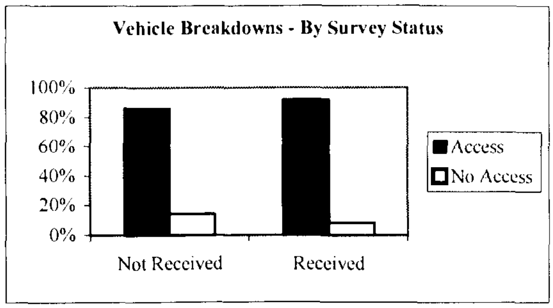

Figure 3.7 - Response bias in vehicle access

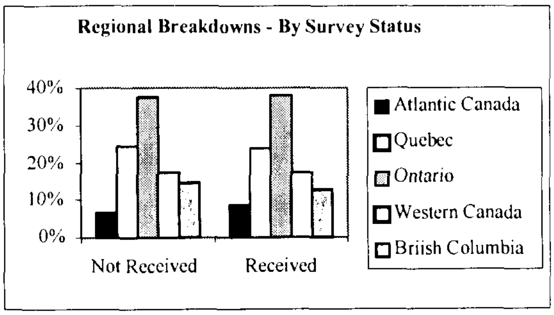

Figure 3.8 – Response bias in regions

3.3.4 Measurement Error

Measurement error is introduced when a respondent interprets a question differently than was intended when the question was designed, making the results for that question much less meaningful. As a result, it is important to test the survey results to ensure that the questions were both understandable, and completable in a reasonable time frame so as to not to overtax respondents. To examine the first of these possibilities, figure 3.9 illustrates how many times each question was skipped (not counting skipped pages), where commonly skipped questions could possibly indicate misunderstandings. Of the 42 question where answers were expected, almost 90% were skipped by less than two percent of respondents, and no question was skipped more than four percent of the time. The questions skipped the most frequently (4 and 41) can both be explained because question 4 mistakenly didn't have a "Don't Know" option, and question 41 asked respondent's about their income.

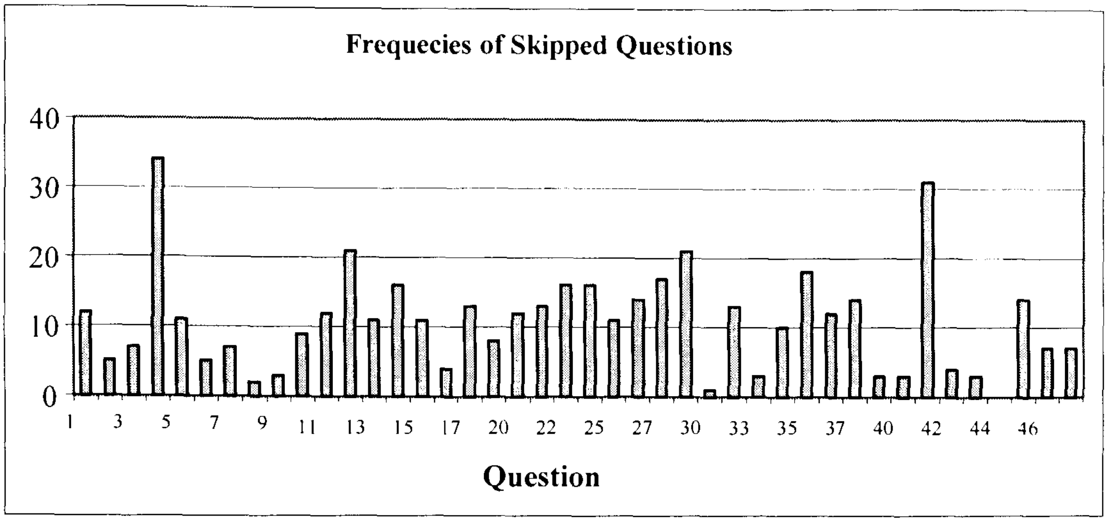

Figure 3.9 – Frequencies of skipped survey questions

Figure 3.9 doesn't show an increase in skipped questions towards the end of the survey, but it doesn't include skipped questions on blank pages, where a higher frequency of missed pages towards the end of the survey could also indicate that respondent's didn't have enough time to complete the survey. To check for this possibility, figure 3.10 shows the times each page was skipped, where pages three/four, and five/six were skipped considerably more than all of the other pages. Although it would have been preferable if no pages had been skipped, the fact that the pages at the end of the survey weren't skipped as often indicates that the survey was probably a reasonable length. A more likely explanation for the skipped pages is that they stuck together, and because they weren't numbered, respondents didn't notice that they had missed a page. The combination of evidence presented in figures 3.9 and 3.10 leads to the conclusion that respondents found both the complexity and time requirements of the survey questions to be reasonable, so the possibility of measurement error is minimal.

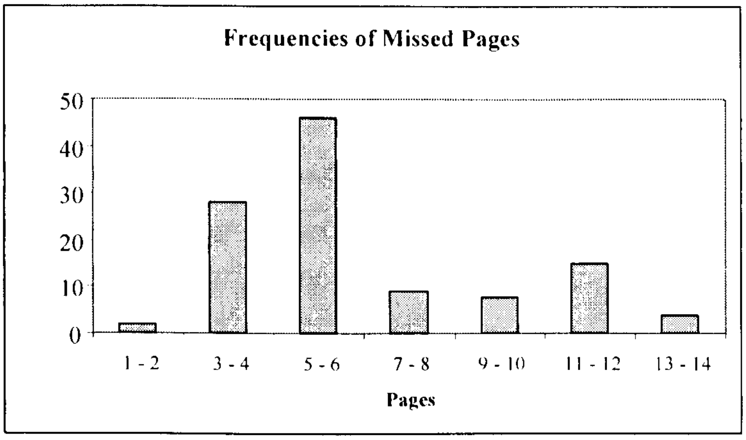

Figure 3.10 – Frequencies of missed survey pages

4 Model Estimation

The respondent choices in questions 20 through 23, and 25 through 28 were used to estimate a variety of multinomial logit models for vehicle and mode choice, where the resulting β parameters were those that best explained the set of data points (choices). The following discussion focuses on these base models, while their adaptation to CIMS is discussed in section 5. The optimal parameter estimates for the entire sample population (section 4.2) are preceded by an introductory examination of the choice questions that illustrates the strengths and weaknesses of the stated preference experiments (section 4.1). Also discussed in this section are some of the alternative MNL models developed from subsets of the survey results (section 4.3), and some techniques to account for the uncertainty surrounding the optimal parameter estimates (section 4.4).

4.1 Preliminary Assessment of Choice Questions

Of the 866 valid surveys received, 3,278 useable vehicle choices and 3,335 useable mode choices were obtained[15] for use in model estimation. Although the overall response rate was excellent, it is also important to ensure that each choice profile was adequately represented. Table 4.1 shows how many of each of the 32 choice profiles in the mode and vehicle choice designs were received, with the average response rate being 108 profiles (75%). Where the least represented profile was returned almost 100 times, all profiles seem to be adequately represented in the returned sample, so all attribute effects can be estimated independently.

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[15] A total of 186 vehicle choice questions, and 129 mode choice questions were eliminated from the possible 3,464 because they weren't answered, or the answer was indiscernible.

Profile	Received
20	118
7	116
2	115
17	114
22	113
26	113
28	113
1	112

Profile	Received
30	112
12	111
13	110
29	110
3	109
9	109
16	109
19	109

Profile	Received
21	109
32	109
23	108
31	108
8	107
11	107
6	106
15	106

Profile	Received
14	105
27	105
18	104
25	101
4	100
10	100
24	99
5	97

Table 4.1 – Counts of received choice profiles

The responses were also examined to see if each alternative received enough choices to reveal the tradeoff points at which that alternative becomes preferred. Figures 4.1 and 4.2 show the total number of choices each alternative received for the vehicle choice, and mode choice experiments, and although the alternative fuel vehicle alternative in the vehicle choice set, and the park and ride alternative in the mode choice set were chosen relatively infrequently in their choice sets (5.2% and 3.5% respectively), neither situation prevented models from being estimated. This conclusions was reached based on Louviere (2000), who explains that equation 4.1 can be used to determine required sample sizes,

$$n \geq \frac{1-p}{p \cdot a^2} \cdot \Phi^{-1}\left(\frac{1+\alpha}{2}\right) \qquad \text{(Equation 4.1)}$$

where n is the minimum required sample size, p is observed market share, a is the desired accuracy, and Φ^{-1} is the inverse cumulative standard normal for significance α. Rearranging the equation to solve for a, with sample sizes of 3,278, and 3,335, market shares of 5.2% and 3.5% can be estimated within 13% and 10% of the true value with 95% confidence. As the observed market shares increase, the accuracy of the estimates also increases considerably.

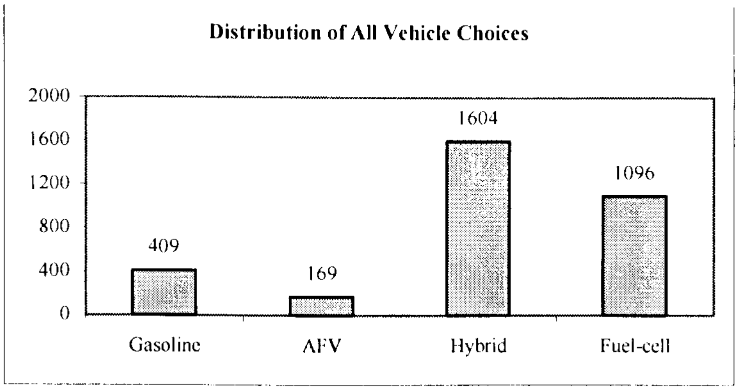

Figure 4.1 – Choice frequencies for each vehicle type

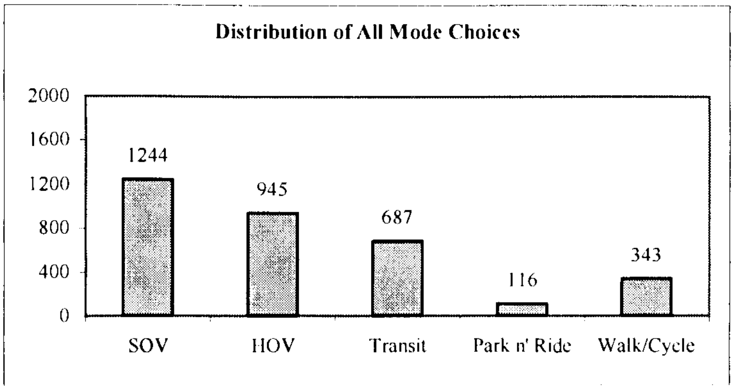

Figure 4.2 – Choice frequencies for each mode type

The final assessment performed on the choice questions was to examine the number of respondents who made the same choice in all four questions on their survey. If this event occurred frequently, the attributes' estimated contribution to utility would be reduced relative to the alternative specific constants, despite the fact that their levels were changing in each choice. Figures 4.3 and 4.4 summarize how many people chose each type of vehicle/mode in all four choices, and how many choose a mixture of vehicles/modes. In both the vehicle and mode choice experiments, 56% of respondents chose the same alternatives in all four questions.

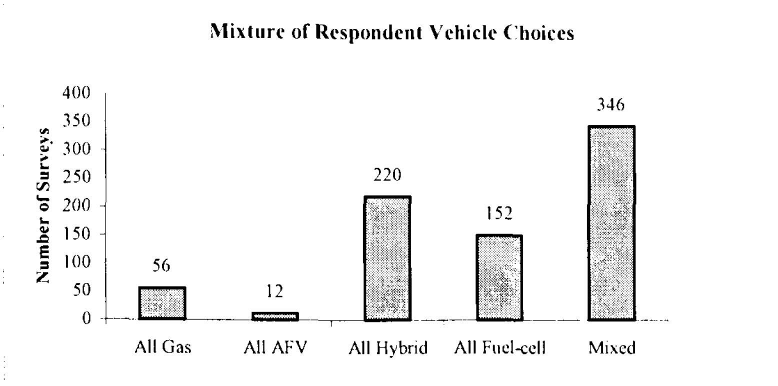

Figure 4.3 – Diversity in respondent vehicle choices

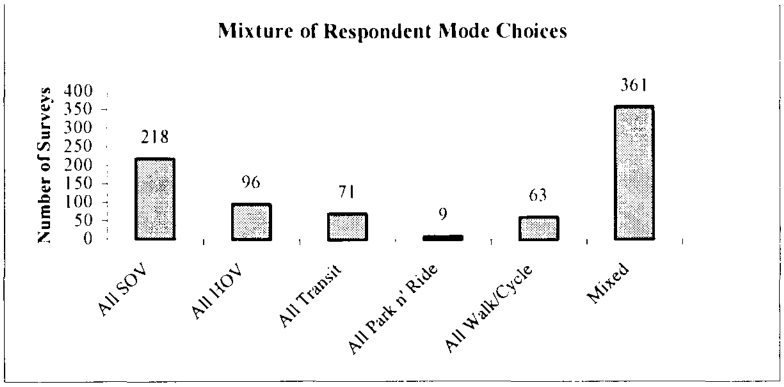

Figure 4.4 – Diversity in respondent mode choices

These high shares can be explained in three different ways. First, the respondents could have taken sufficient time to read and understand each question, but the majority associated a high utility with the alternative they selected based on something other than the attributes presented. This is the preferred explanation, because although it means some important factors may have been missing from the choice experiment, each answer is still independent, and the estimated models would be valid representations of the respondents' views. A second explanation is that the respondents may not have spent enough time reading the questions, and as a result failed to notice that the attribute levels were changing from question to question. If this were true, the observations for each individual wouldn't be independent, and the majority of the choice observations would be invalidated. Third, it's possible that the respondents were overwhelmed by the number choices and attributes, and therefore had to focus on just a small subset of the possibilities in order to make their decision. This outcome would not be as serious as the second because the choices would still be independent, but the models would be biased because all attributes are assumed to have the same potential to influence the decision, regardless of the decision maker. Based on a sampling of survey comments, all three of these possibilities seem to be defendable, but the first seems to be the most common explanation. The general high quality to which the rest of the survey was completed indicates that people did take the time to think about the questions, and there were only a few comments saying that the questions were confusing or overwhelming.

4.2 Estimated Models Using the Complete Sample

As mentioned, multinomial logit models are estimated using maximum likelihood techniques, which maximize the log of the likelihood function, L,

$$L = \sum_{q=1}^{Q} \sum_{j=1}^{J} f_{jq} \ln P_{jq} \qquad \textit{(Equation 4.2)}$$

where f_{jq} is 1 if alternative j was chosen in observation q and 0 otherwise, and P_{jq} is the probability of observation q choosing alternative j, which is equivalent to the multinomial logit market share calculation given in equation 2.6. The non-logged likelihood function would be the product of the different P_{jq} terms, but by taking the natural logarithms, the product is converted to a sum, and the rounding errors that would occur otherwise are avoided. The set of β parameters used in P_{jq} that yield the largest sum of choice probabilities are the maximum likelihood estimates for a given utility formulation and set of observations. LIMDEP version 7.0 was used to find the MLE's of the parameters for both the mode and vehicle choice models.

4.2.1 Vehicle Choice

The utility for each vehicle type, V, was estimated according to equation 4.3

$$V = \beta_{CC} \cdot CC + \beta_{FC} \cdot FC + \beta_{FA} \cdot FA + \beta_{EXP} \cdot EXP + \beta_{POW} \cdot POW + \beta_{ASC} \qquad \textit{(Equation 4.3)}$$

where CC is capital cost, FC is the monthly fuel cost, FA is the percentage of service stations with the required fuel, EXP indicates if the vehicle has access to express lanes (0) or not (1), POW indicates if the vehicle has power equal to (0) or 10% less than (1) the respondent's current vehicle, and ASC is a constant specific to each alternative. The first five β parameters are constrained to be identical for the four vehicle types (for example, capital cost is equally important for each vehicle type), but the β_{ASC} term can be different for each vehicle[16]. Table 4.2 shows the results of this model using all 3,278 observations, with the MLE estimates for the weighting coefficients appearing in the second column, and the t-values in the third column. It should be noted that emissions were not included as a variable in the utility formulation because although respondents were given emissions information, the attribute levels were constants in the experimental design, and as such, any resulting effect can't be distinguished from the alternative specific constants.

Beta Parameter	**MLE**	**t-value**
Capital Cost	-9.01E-05	-5.76*
Fuel Cost	-4.60E-03	-3.38*
Fuel Availability	1.16	8.47*
Express Lane Access	-0.16	-3.09*
Power	-0.22	-4.47*
ASC – Gasoline	-1.70	-17.22*
ASC – Alternative Fuel	-2.01	-23.06*
ASC – Hybrid Electric	-0.36	-4.18*
Log-likelihood - full model	-3,625.61	
Log-likelihood - constants only	-3,699.51	
Log-likelihood - no coefficients	-4,544.27	
Observations	3,278	

*Coefficient is significant with 99% confidence.

Table 4.2 – Best fit statistics for vehicle choice model

All of the parameters have the expected sign, with increased capital, and increased fuel costs having a negative impact on utility, while increased fuel availability, increased express lane access, and increased power all had a positive impact on utility. All of these coefficients, and the three alternative specific constants were significant with 99% confidence (when the value in the third column exceeds ±2.57). The explanatory power of discrete choice models is commonly tested by comparing the cumulative log-likelihood of the base model (4th last row) against models with no coefficients (2nd last row), and models just containing alternative specific constants (3rd last row). The test statistic for these comparisons is two times the difference in the models' cumulative log likelihoods, which approximately follows a chi-squared distribution, with the number of

[16] To facilitate model estimation, the alternative specific constant for the fuel cell vehicle was fixed at zero.

degrees of freedom equaling the number of coefficients that have been restricted. Both test statistics (1,837.3 for the no coefficients, and 147.8 for the just alternative specific constants) resulted in a rejection of the null hypothesis, meaning that the model presented in table 4.2 offers an improved explanation of the data than either of the alternatives with 99% significance.

An important comment about the alternative specific constants is that their magnitudes are relatively large compared to the other attributes' contributions to utility. This means that the alternative specific constants will constitute a significant share of the total observed utilities whatever values the attributes take on, and as a result, they will potentially become the primary determinants of market share. For example, in a scenario where a gasoline vehicle possessed the attributes summarized in table 4.3, 47% (-1.49) of the observed utility is the result of the attributes, compared to 53% (-1.70) from the alternative specific constant.

Attribute	**Value**
Capital Cost	$20,000
Fuel Cost	$150 / month
Fuel Availability	100%
Access to Express Lanes	No
Power Compared to Current Vehicle	Equal

Table 4.3 – Attribute values for gasoline vehicle

Although the alternative specific constants account for a significant portion of the observed utilities, the magnitude of the observed utilities needs to be assessed relative to the error term to know what influence they will have on the market shares. If the scale of the model is large, meaning that the observed utility is large compared to the error term, the attributes and alternative specific constants will strongly influence the market shares. If the scale of the model is small however, neither the attributes nor the alternative specific constants will influence market shares (regardless of their relative magnitudes). Instead, the market shares will be dictated by the error terms, and because all of the error terms are identical in a multinomial logit model, the predicted market shares would also be equal. In order to assess the scale of the vehicle choice model, it was compared with similar models produced by Bunch (1993), and Ewing (2000). Since the exact specification of attributes differs from model to model, this task was accomplished by comparing the coefficients for capital cost in the different models. Examining the base models from Bunch's and Ewing's work revealed their coefficients for capital cost were 2.2 and 1.5 times larger than the coefficients in this study's model. The larger coefficients indicate that the scale of their models is larger, and that the attributes and alternative specific constants would therefore have more influence on the market shares[17].

With this understanding, the following analysis illustrates the impact that the model's scale, and the relative magnitude of its attributes and alternative specific constants have on predicted market shares. High and low values were selected for each attribute (shown in table 4.4), and then combined to create a high and a low utility scenario for each vehicle type. This process resulted in eight different vehicles (an attractive and unattractive version for each type). To test how much market share each vehicle type could obtain, its attractive (high utility) version was combined with the low utility versions of the other three vehicle types. The reverse was done with each vehicle's unattractive (low utility) version to test how small a market share each type could obtain. The process resulted in eight scenarios in which each vehicle type was as attractive and unattractive relative to the other vehicle types in one scenario. The ranges shown in figure 4.5 show what market shares are possible for each of the vehicle types in these high and low utility scenarios.

Attribute	**Low Utility Value**	**High Utility Value**
Capital Cost	$40,000	$20,000
Fuel Cost	$225 / month	$75 / month
Fuel Availability	25%	100%
Access to Express Lanes	No	Yes
Power Compared to Current Vehicle	10% Less	Equal

Table 4.4 – Attribute values used to produce high and low vehicle type utilities

[17] This conclusion assumes that all people value capital cost the same regardless of the sample population's demographics. An alternative conclusion could be that the sampled population for the given study just placed a higher importance on capital cost, and the other attributes might compare differently. This complete test was not possible because beyond capital cost, the exact attributes differed from model to model.

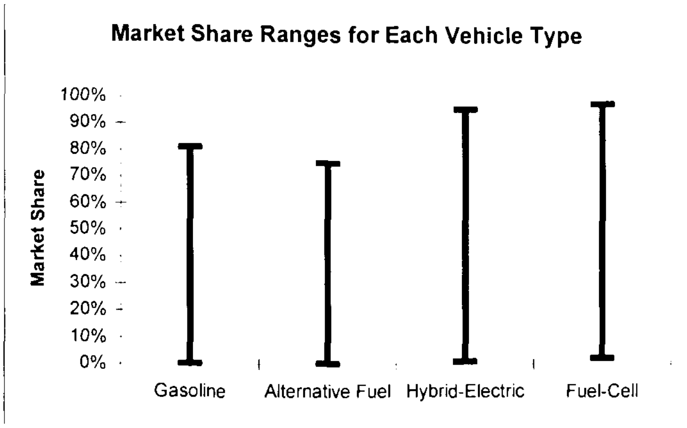

Figure 4.5 – Possible vehicle type market shares

These market share ranges do not represent absolute minimums or maximums, because the attribute values could be set to cover a wider range, but they do illustrate two key points. First, although the model's scale is smaller than some similar models, the attribute coefficients and alternative specific constants are large enough to prevent the error terms from dominating total utility, and they allow a considerable range of market shares to be predicted. At the same time however, for the range of attribute values considered, the magnitude of the alternative specific constants prevents most vehicle types from being able to capture the full range of possible market shares (0% to 100%). For example, the gasoline vehicle is unable to achieve more than 80% market share, even when all of its attributes are superior to the other vehicle types because the alternative specific constants for the hybrid electric and hydrogen fuel cell vehicles are so much larger than gasoline's. These findings are encouraging, because they contradict DeCanio and Laitner's (1997) conclusions that estimating these types of models leads to alternative specific constants that prevent emerging technologies from capturing significant market share. In this vehicle choice model, the reverse problem seems to actually be present to a minor degree.

Focusing specifically on the alternative specific constants for the different vehicle types reveals another interesting finding, where all else being equal, respondents actually had an attraction to the less familiar, non-gasoline vehicles. Hydrogen fuel cell vehicles were the most popular, followed by hybrid electric vehicles, and then gasoline and alternative fuel vehicles. Figure 4.6 shows predicted market shares for the four vehicle types if each possessed identical characteristics except for the alternative specific constants. This finding shows that those surveyed don't seem to be worried about experimenting with new engine technologies if the vehicle performance is otherwise comparable to existing options. Ewing (2000) reached similar conclusions when he examined the preferences of Montreal commuters for gasoline, alternative fuel, and electric vehicles.

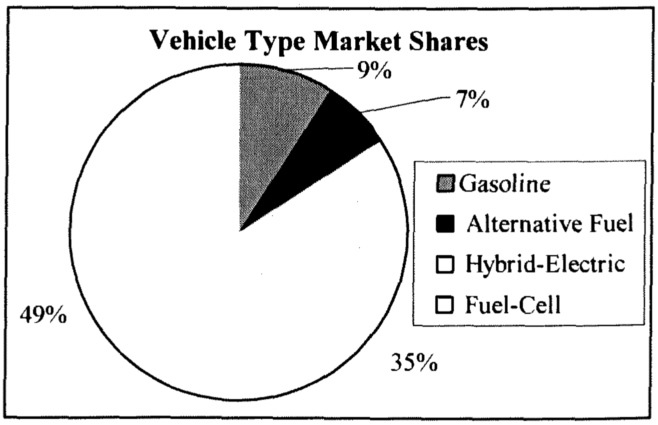

Figure 4.6 – Vehicle type market shares based on equal attribute values

An obvious problem with these conclusions is that non-gasoline vehicles haven't gained significant new market share anywhere in Canada, and certainly not to the levels shown in figure 4.6. This can be explained in part because the attribute values for non-gasoline vehicles have been set to extremely attractive levels to produce these market shares predictions, so they might be realistic if attribute values reached these levels in some future scenario. However, the answer is not this simple, as non-gasoline vehicles continue to gain significant market share even when attribute levels are set to values closer to those currently experienced by survey respondents. At these levels, upwards of 70% of respondents said they would choose a hybrid-electric vehicle, when in reality only one of the 781 respondents with vehicle access had done so. Question six in the survey was designed to help explain the differences in alternative specific constants by asking respondents to rate the importance of eight different vehicle attributes (five of which, were not attributes in the vehicle choice experiment). As shown in figure 4.7, reliability, safety, and vehicle type were the most important attributes that weren't included as attributes in the discrete choice survey. Unfortunately, these results don't help explain the rankings of the alternative specific constants because there is no reason to believe respondents would have rated non-gasoline vehicles to be superior in these attributes. They were instructed that all of the vehicle types were the same class, and given their limited knowledge about hydrogen fuel cell and hybrid vehicles, it seems more likely that they would assume non-gasoline vehicle to have reduced reliability and safety.

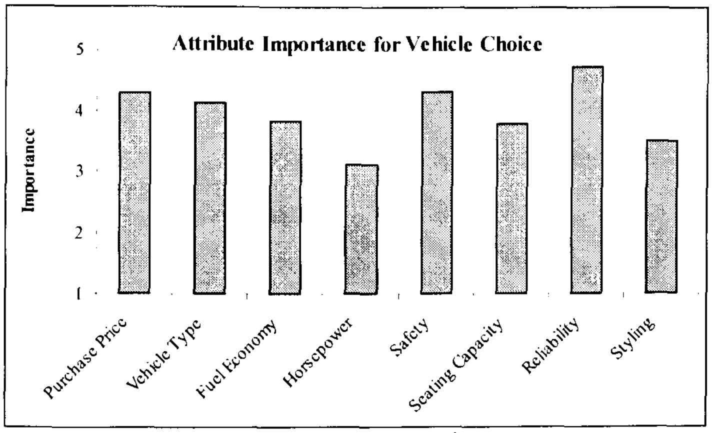

Figure 4.7 – Attribute Importance in Vehicle Choice

The attractiveness of non-gasoline vehicles could be explained in two additional ways. First, nothing in the statistical models accounts for the number of vehicle models available, when in reality far more than four alternatives exist, and most of the additional models are gasoline vehicles. Leiby and Rubin's (2001) model of vehicle choice includes indicators for both the number of makes and models of different vehicle types, and these factors are some of the most important determinants of vehicle type market shares. Second, it is also possible that the alternative specific constants are artificially large because respondents said they would pay more for emission reductions than they would actually pay in reality. With the exception of the alternative fuel vehicles, the ranking of the alternative specific constants paralleled the ranking of emissions reductions for each vehicle type, so this explanation seems to be plausible. Bunch et al. (1993) did vary emissions levels in their experimental design, and they found emissions reductions to have a positive influence on utility, but they questioned the believability of this conclusion on the basis that the results were artifacts of the stated preference study, and wouldn't have been found using revealed preferences. Similarly, Johansson-Stenman, and Martinsson (2002) found in a survey of 2,500 Swedish car owners that survey respondents consistently (and unconsciously) overstated their concern for the environment when asked to rate its importance in their decisions. Both of these explanations make sense intuitively, and techniques to account for them are discussed in section 5.2.

The remaining attributes also play an important role in each vehicle's utility, but it is difficult to directly compare them because their influence is dependant on the changes in attribute level, and none of the units are equivalent. Table 4.5 displays how much of each attribute would be equivalent to a $1,000 increase in capital costs. For example, a consumer would be willing to accept the capital cost being $1,000 more if fuel costs were decreased by $19.59 per month. Under this presentation format, a direct comparison is still difficult, but one interesting observation is the relative unimportance of express lane access. Only an 8% increase in availability or a 4% increase in power is required to compensate a $1,000 increase in capital cost, whereas a 56% increase would be required for express lane access. Although it is quite possible that respondents placed a much higher importance on fuel availability and power, an alternate explanation that should be considered is that their limited knowledge of express lanes caused respondents to marginalize the attribute. In total, 83% of respondents either didn't have access to, or didn't know what a carpool express lane was, so they may not have understood the attribute well enough to give it significant weighting in their decisions.

Attribute	**Change Equal to $1000 Increase in Capital Cost**
Fuel Cost	$-19.59 / month
Fuel Availability	+ 8%
Express Lane Access	+ 56%
Power*	+ 4%

*Value indicates 4% or total power, not 4% of 10%.

Table 4.5 – Capital cost equivalency for vehicle attributes

When changes in attribute values don't offset each other, market shares will be altered, and the magnitude of that change will depend on both the initial market share and the initial attribute value of the technology being altered. This dependence results from the multi-nomial logit's non-linear market share curve, which is steep (high elasticity) when utilities are similar, and flat (low elasticity) when utilities are different. Typically, a technology's market share elasticity, E, is expressed as the percent change in the technology's market share resulting from a percent change in one of its attributes (equation 4.4). Alternatively, equation 4.5 shows how the numerator can be expressed as the change in market share instead of percent change, yielding an elasticity defined as E^*.

$$E = \frac{\%\Delta MS}{\%\Delta X_i} \qquad \textit{(Equation 4.4)} \qquad\qquad E^* = \frac{\Delta MS}{\%\Delta X_i} \qquad \textit{(Equation 4.5)}$$

When this second form of elasticity is calculated for a multinomial logit model with a linear-additive utility formulation, equation 4.6 results,

$$E^* = \beta \cdot X_i \cdot MS_i \cdot (1 - MS_i) \qquad \textit{(Equation 4.6)}$$

where β is the weighting coefficient of the attribute being changed, X_i is technology i's value for that attribute, and MS_i is technology i's initial market share.

Because the attribute weighting coefficients are equal for each vehicle type, equation 4.6 will also produce the same results for each vehicle type with a given X_i and P_i, so the following elasticity curves apply to all of the vehicle types. Figures 4.8 through 4.12 show E^* for the five vehicle choice attributes at four different attributes values. Examining each figure individually, the largest changes in market share occur when a vehicle is capturing 50% of the market, which is the steepest point in the market share curve. Also, larger initial attribute values lead to larger changes in market share because market shares are calculated based on absolute differences, so a percent change is larger for larger initial values. Comparing across figures, changes in capital cost result in the largest changes in market share, followed by similar effects for fuel costs and fuel availability, with the smallest impacts resulting from express lane access.

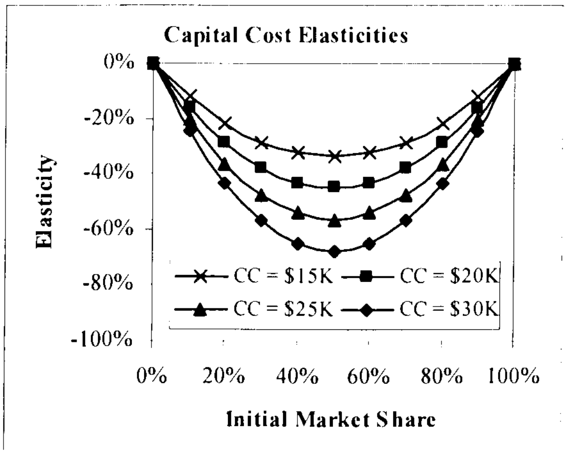

Figure 4.8 – Capital Cost Elasticities

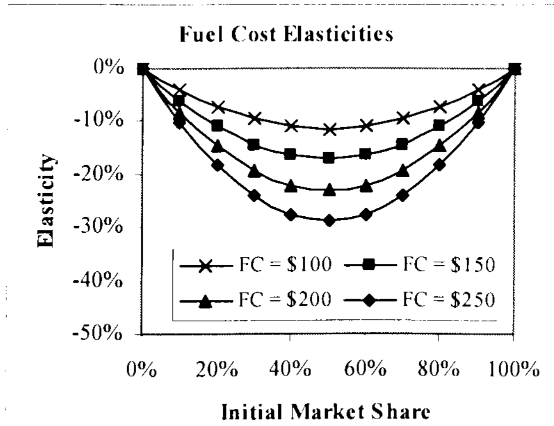

Figure 4.9 – Fuel Cost Elasticities

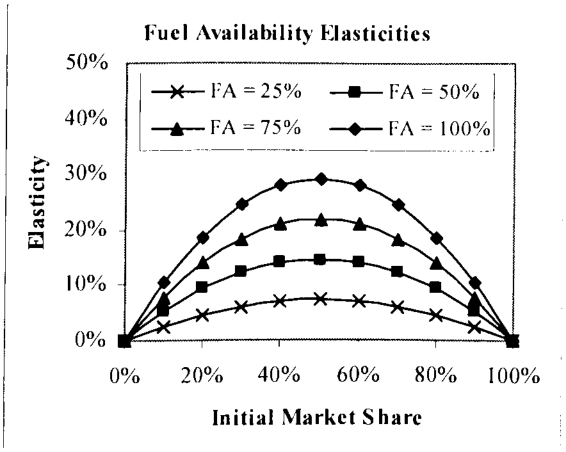

Figure 4.10 – Fuel Availability Elasticities

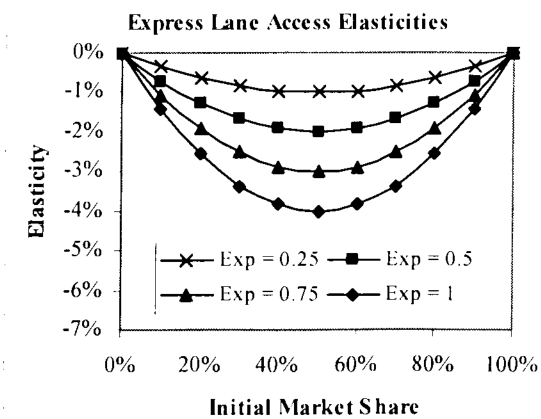

Figure 4.11 – Express Lane Access Elasticities

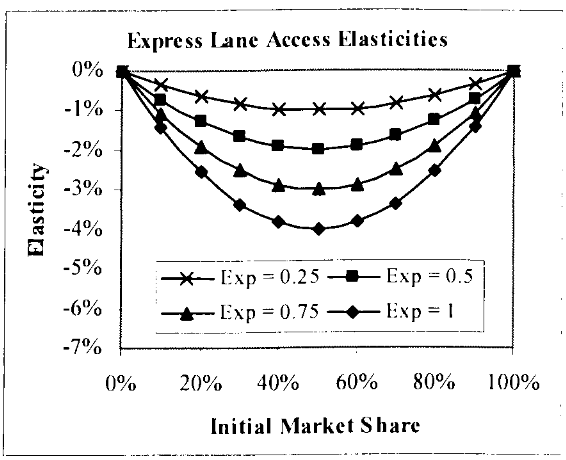

Figure 4.12 – Power Elasticities

4.2.2 Mode Choice

Unlike the vehicle choice model, the utility of each mode, V_{MODE}, has a unique formulation, as shown in equations 4.7 through 4.11.

$$V_{SOV} = \beta_{DT} \cdot DT + \beta_{COST} \cdot COST + \beta_{SOV} \quad \text{(Equation 4.7)}$$
$$V_{HOV} = \beta_{DT} \cdot DT + \beta_{PDT} \cdot PDT + \beta_{COST} \cdot COST + \beta_{HOV} \quad \text{(Equation 4.8)}$$
$$V_{TRANSIT} = \beta_{DT} \cdot DT + \beta_{WWT} \cdot WWT + \beta_{COST} \cdot COST + \beta_{TRANS} \cdot TRANS + \beta_{TRANSIT} \quad \text{(Equation 4.9)}$$
$$V_{PARK} = \beta_{DT} \cdot DT + \beta_{WWT} \cdot WWT + \beta_{COST} \cdot COST + \beta_{TRANS} \cdot TRANS + \beta_{PARK} \quad \text{(Equation 4.10)}$$
$$V_{WC} = \beta_{DT} \cdot DT + \beta_{PATH} \cdot PATH + \beta_{WC} \quad \text{(Equation 4.11)}$$

where DT is the driving time, PDT is the pickup and drop-off time, WWT is the walking and waiting time, COST is the monthly cost of the mode, and TRANS is the number of transfers required. Anywhere a β parameter occurs in more than one utility formulation (β_{DT} and β_{COST} for example) the estimated value is the same for all occurrences. It should also be noted that the alternative specific constant for the walking and cycling option is fixed to zero because a maximum of four of the five alternatives can be varied during model estimation. In addition to the utility formulations presented above, some alternate forms were experimented with (allowing the value of driving time to be different for each mode for example), but the model presented in this section seemed to provide the best combination of explanatory power, and simplicity. Table 4.6 shows the MLE parameters and t-values when the above equations were estimated using all 3,335 mode choices.

Beta Parameter	**MLE**	**t-value**
Cost	-2.84E-03	-5.29*
Driving Time	-4.42E-02	-13.84*
Pickup/Drop-off Time	-7.94E-02	-5.07*
Walking/Waiting Time	-7.32E-02	-8.36*
Transfers	-0.16	-2.00**
Cycling Path	0.17	1.26***
ASC – SOV	-0.53	-3.94*
ASC – HOV	-0.47	-2.73*
ASC – Transit	-0.46	-3.02*
ASC - Park n' Ride	-1.95	-10.80*
Log-likelihood	-4,088.34	
Log-likelihood - constants only	-4,673.59	
Log-likelihood – no coefficients	-5,367.48	
Observations	3,335	

*Coefficient is significant with 99% confidence.
**Coefficient is significant with 95% confidence.
***Coefficient is significant with 80% confidence.

Table 4.6 - Best fit statistics for mode choice model

As with the vehicle choice model, all of the attributes entered the model with the expected signs. Increasing time, cost, and the number of transfers had a negative influence on utility, with only increasing access to bike routes having a positive effect, and the estimates were each significant with 99% confidence, with the exception of the number of transfers (95%), and the presence of cycling paths (80%). Despite the lower confidence in the cycling path parameter, it has been left in the main model because a number of comments on surveys indicated that people felt positively about bike routes, and the lower confidence is partially the result of the smaller sample size of cycling choices. The log-likelihood ratio statistics for the just constants model (1,170), and no coefficients model (2,558) both exceed their respective chi-square distribution values, indicating that the parameter estimates in table 4.6 offer greater explanatory values than those with the restricted parameter sets.

Prediction ranges for possible mode market shares are dictated by two factors: the attributes' and alternative specific constants' relative contributions to utility, and the relative magnitudes of the observed utility and the error term. The range of market shares possible for each mode type was tested using the same procedure described for the vehicle choice model, with the high and low attribute values shown in table 4.7. These attribute values are well within the ranges of values presented in the surveys, and as the resulting market share ranges in figure 4.13 show, market shares from 0% to almost 100% are possible for each of the modes. These results show that like the vehicle choice models, the observed component of utility is large enough relative to the error terms to allow the market share predictions to be influenced by realistic attribute values. Unlike the vehicle choice models however, the alternative specific constants in the mode choice utility formulations are not as dominant relative to the attributes' contributions to utility. In other words, almost a full range of market shares is possible for each of the modes because of the alternative specific constants' smaller relative magnitude.

Attribute	Low Value	High Value
Cost	$50 / month	$200 / month
Driving Time	5 minutes	60 minutes
Pickup/Drop-off Time	0 minutes	20 minutes
Walking/Waiting Time	0 minutes	20 minutes
Transfers	0	1
Cycling Route Access	No	Yes

Table 4.7 – Attribute values used to produce high and low mode type utilities

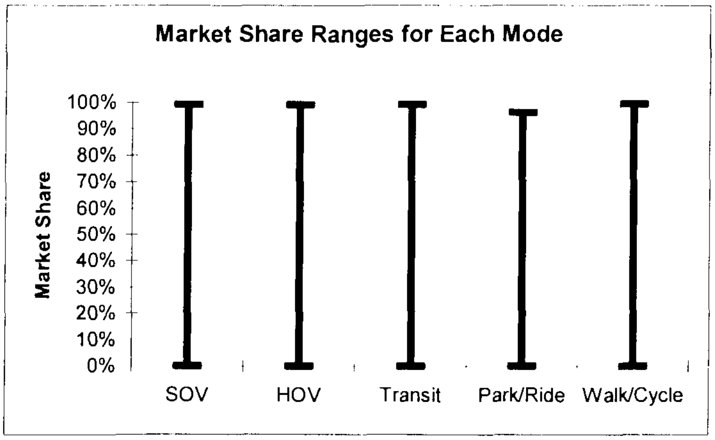

Figure 4.13 -- Range of possible market shares for each mode

Figures 4.14 and 4.15 show the actual and predicted market shares for the five modes, where the actual shares were obtained from survey responses, and the predicted shares were based on the costs and times provided by respondents in their survey responses. The detailed attribute values for each of these scenarios can be found in appendix 5. Given that it was difficult to know the exact level of some attributes (respondents weren't asked to decompose the time of their commutes for example), the two figures seem to match fairly well. The major divergence between the actual and predicted shares occurs with the carpooling option, which is predicted to be almost four times as popular as it is in reality. A possible explanation for this problem is that some respondents chose the carpooling option in the choice experiment, when in reality it was not a possibility for them. This possibility is supported by some survey comments, which indicated that carpooling was not a feasible option, even though it had been selected. If the carpooling option is eliminated for the 39% of the population that claimed it was not available to them, its share drops to 16%, which is much closer to the actual share. The issue of mode availability is discussed further in section 6.

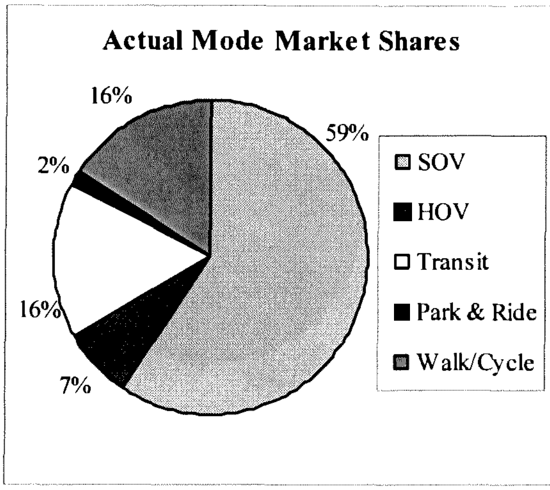

Figure 4.14 – Actual mode shares for respondents

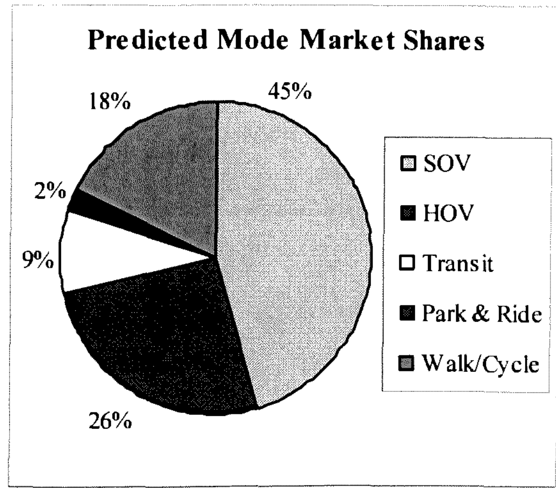

Figure 4.15 – Predicted mode shares for respondents

Taking a closer look at the alternative specific constants reveals that the values for the SOV, HOV, and transit options are all relatively similar, while park and ride was the least attractive, and walking and cycling was the most attractive. In a scenario where the costs and times of the different modes (with the exception of walking and cycling) were quite competitive, the similarity of the alternative specific constants for SOV, HOV, and transit means that each mode will obtain considerable market share. The results of such a scenario are displayed in figure 4.16, with the exact attribute values available in appendix 5. The aversion to using park and ride services can possibly be explained because many respondents were unfamiliar with the option (the service was either unavailable or unknown to 61% of respondents compared to 2% for SOVs), and as a result they were hesitant to select it even though the attributes may have been attractive. The attraction to walking and cycling makes sense because many of the attributes associated with walking and cycling, such as personal health and environmental benefits were not included in the survey, so they are accounted for in the alternative specific constant.

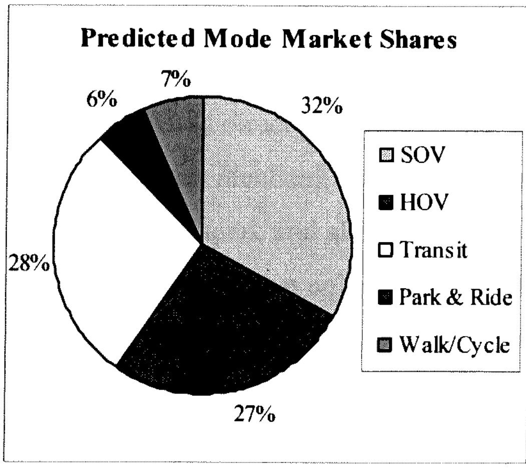

Figure 4.16 – Market Shares for scenario with similar times and costs

The results of survey question 13 were designed further explain the relative rankings of each alternative specific constant by asking respondents how they rated eight different mode attributes (six of which, weren't included in the experiment design). Interestingly, the results in figure 4.17 show flexibility, safety, and reliability were the most important attributes excluded from the mode choice experiment. These would all seem to be attributes that favor SOV travel, and they do little to explain why carpooling and transit were rated equivalently in the model. Environmental impact is an attribute that would favor non-SOV modes, but it was not rated as a particularly important attribute in the survey. Two additional factors that may explain this difference are the companionship possible in non-SOV modes, and the ability to work on other tasks. Based on survey comments, these factors would seem to be important to some respondents, but unfortunately, no questions in the survey specifically targeted these attributes.

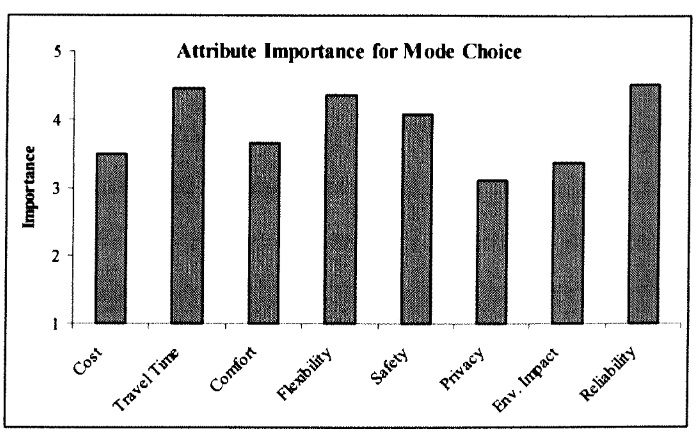

Figure 4.17 – Attribute Importance in Mode Choice

The mode choice models have three variables describing time (driving time, walking/waiting time, and pickup/drop-off time), and because the units are identical, they can be compared directly. Interestingly, the respondents' valuations of the different types of time were not identical, with the coefficients for the non-driving time attributes approximately equal, and almost twice as influential as the driving time attribute. This means for example, that an average respondent considers spending half an hour driving to work to be roughly equivalent to waiting for 10 minutes, and then driving for another 10 minutes. So although the absolute time involved in these non-driving activities may be small relative to the entire commute, their influence on respondent choice, and therefore their role in policy, can be significant. A number of other mode choice studies (Washbrook, 2002, Asenio, 2002, and Bhat, 1997 for example) have reached the same conclusion that traveling time is more bearable then non-driving time, although it should be noted that the values they observed for different types of non-driving time often had different relative rankings. The only counter conclusion found in the literature belonged to Train (1979), in which in vehicle time was found to be slightly more important than waiting time (carpooling was not examined).

The elasticities for the six mode choice attributes are displayed in figures 4.18 through 4.23. As with the vehicle choice experiment, the elasticities are presented as the change in market share over the percent change in attribute values, with four initial values shown for each attribute. The three figures for time-based attributes reinforce the conclusions of the preceding paragraph, with pickup/drop-off and walking/waiting time elasticities being relatively equal, and approximately twice as important as driving time. This can be seen by comparing the lines marked by triangles (time = 15 minutes) on figures 4.20 and 4.21 with the line marked by squares (time = 30 minutes) on figure 4.19. The figures also show that time seems to be a more important determinant of choice than cost, and that both cycling route access and the number of transfers have similar but much smaller impacts on market share than the time and cost attributes.

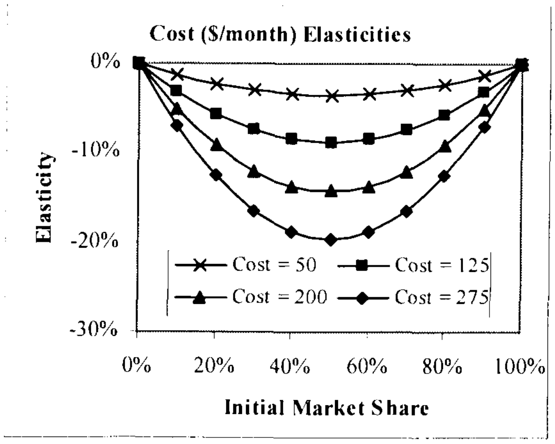

Figure 4.18 – Cost Elasticities

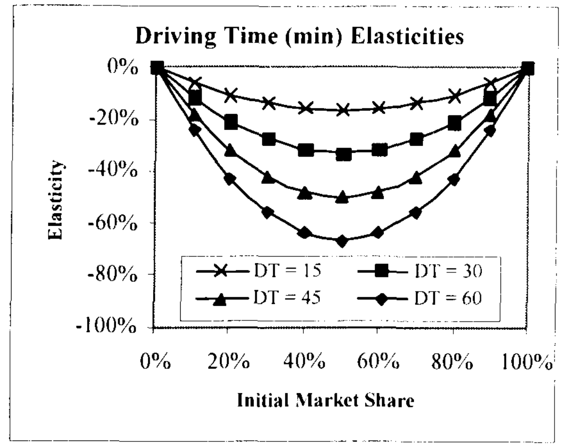

Figure 4.19 – Driving Time Elasticities

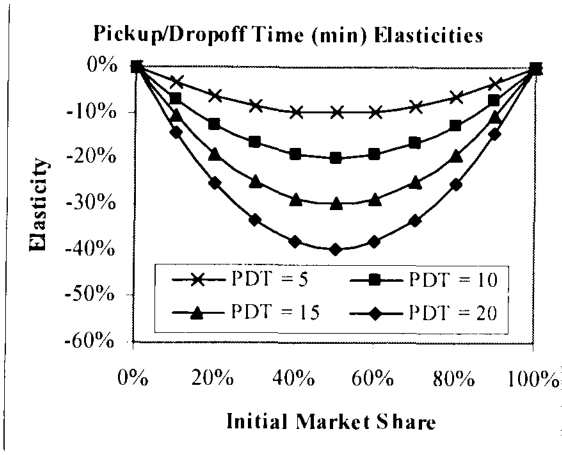

Figure 4.20 – Pickup/Drop-off Time Elasticities

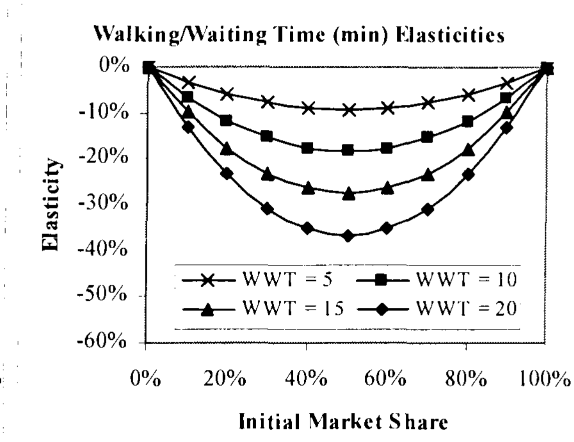

Figure 4.21 – Walking/Waiting Time Elasticities

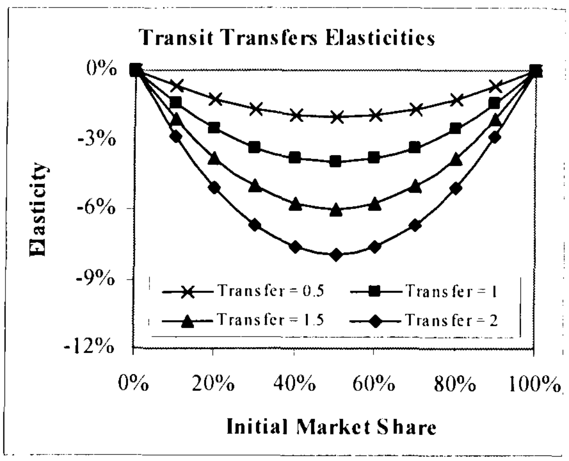

Figure 4.22 – Transit Transfers Elasticities

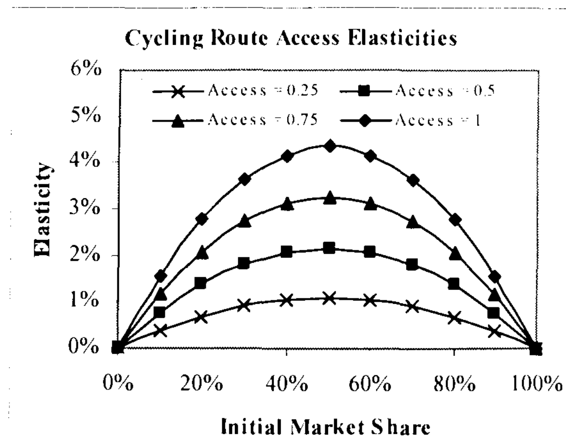

Figure 4.23 – Cycling Route Access Elasticities

4.3 Estimated Models Using Segmented Samples

The models discussed to this point have all included the full sample of respondents, without any attempt to disaggregate the results based on different demographic indicators. Different segments of society commonly hold different views, and the models estimated for these different populations would presumably also be different. For example, income and gender have commonly been interacted in utility formulations to allow market share predictions to vary across different populations (Bunch, 1993 and Ewing, 2000 provide vehicle choice examples). Although these segmentations can be informative, they are not particularly useful for a model like CIMS, because there is no means of distinguishing between different populations (except on a regional basis). As such, the following discussions of sub-models for vehicle choice and mode choice are primarily to illustrate the potential for model misspecifications by not having demographic differences represented within CIMS.

4.3.1 Vehicle Choice

In addition to the vehicle choice model based on all 3,278 observations, eight sets of sub-models were estimated according to the same utility formulation presented in equation 4.3, to yield 32 individual sub-models. The segments were based on region, city size, major cities, age, gender, education, family income, vehicle access, and vehicle type. Each set of sub-models can be compared with the base model, using the same test that compared the base model against those with no coefficients. The test statistic is two times the difference between the cumulative log likelihood of the base model, and the sum of cumulative log likelihoods for a set of sub-models (all five regions for example). This statistic follows a chi-squared distribution, with the number of degrees of freedom equal to the number of coefficients summed across sub-models minus the number of coefficients in the base model. The only caveat to this procedure is that the cumulative sample sizes for the sub-models need to equal the sample size for the entire population. In the cases where some respondents didn't fit into a category (some people didn't provide an income for example) the log likelihoods were scaled up to be comparable to a sample size of 3,278[18]. The results of these tests are displayed in table 4.8, and with the exception of the major cities segmentation all of the sub-models offered greater explanatory power than the base model with 99% confidence.

Segment	Sub - Models	Test Statistic	Degrees of Freedom	Reject Null Hypothesis*
Region	5	88.4	32	Yes
City Size	3	68.9	16	Yes
Major Cities	3	-24.5	16	No
Age	4	92.5	24	Yes
Education	4	113.8	24	Yes
Gender	2	55.3	8	Yes
Income	5	113.7	32	Yes
Vehicle Type	4	57.3	24	Yes

*Models were significantly different with 99% confidence

Table 4.8 Significance of vehicle choice demographic segments

As groups, almost all of the segmentations explain the observed vehicle choices better than the base model, but not all of their individual sub-models necessarily make sense intuitively. For example, in the region sub-models, only two of the five sub-models had all five coefficients with the expected sign, and none of the models had eight significant coefficients. Table 4.9 summarizes how many times each attribute coefficient had the expected sign and was significant, and as can be seen, none of the coefficients were significant in all 32 sub-models, and two of the five attribute coefficients didn't have the expected sign all the time. The fact that the fuel cost coefficient is not the expected sign in seven of the 32 sub-models[19] is of particular concern because it is difficult to explain why increasing fuel costs would have a positive influence on utility. Also of note is that both the express lane access, and ASC for hybrid vehicles weren't significant in very many sub-models (12 and 17 respectively), so although they were significant in the base case, confidence in those estimates should be cautioned.

[18] Strictly speaking, this step is not mathematically correct, but due to the small number of missing samples (less than 3%), the error introduced was deemed to be negligible.
[19] In all seven of these cases, the fuel cost coefficient was not significantly different from zero, but the most likely estimate was still a positive value.

Coefficient	Times expected sign was observed	Times coefficient was significant*
Capital Cost	32	26
Fuel Cost	25	22
Fuel Availability	32	27
Express Lane Access	29	12
Power	32	22
ASC – Gasoline	na	31
ASC – AFV	na	31
ASC – HEV	na	17

*With 95% confidence

Table 4.9 – Summary of coefficients in vehicle choice model segments

Recognizing that the sub-models have some problems, table 4.10 presents more detailed information on each of the individual sub-models, while the complete parameter estimates and t-statistics are available in appendix 6. Some of the most noteworthy segments are those based on age, education, and gender, which all have the expected signs in all of their sub-models. In these three segmentations, some of the differences between sub-models followed distinct trends, whereas others seemed to be patternless. In the age segments, vehicle power and access to proper fuel had less importance for older respondents, which could be the result of older respondents having less interest in driving long distances, and a decreased desire for powerful vehicles. In the education segments, access to the proper fuel was more important for people with more education, perhaps because they were more likely to be traveling longer distances. Interestingly, higher education leads to a greater importance being placed on vehicle power, which contradicts the findings of Ewing (2000), and Bunch (1993), who both find increased education leads to increased environmental concern. This finding also seems to contradict other model results that show respondents with a higher education also had the greatest aversion to gasoline vehicles compared to the cleaner hybrid electric, and hydrogen fuel cell vehicles. Finally, when looking at the gender segments, women place less importance on power than men, and they also place a much higher value on the operating costs relative to the other attributes.

Sub-Model	Obs.	CLL	Expected Signs	Significant Coefficients*
All Observations	3278	-3625.6	5	8
Region – Atlantic	286	-310.5	3	4
Region – Quebec	772	-867.0	5	6
Region – Ontario	1226	-1334.8	5	7
Region – Prairies	583	-622.5	4	5
Region – BC	411	-446.5	4	4
City Size – More than 1,000,000	1670	-1875.3	5	8
City Size – 500,000 to 1,000,000	924	-973.4	5	6
City Size – Less than 500,000	684	-742.5	3	5
City – Toronto	709	-780.5	5	6
City – Vancouver	353	-373.6	4	3
City – Montreal	608	-699.2	5	5
Age – Younger than 25 years	300	-283.0	5	8
Age – 26 to 40 years	1053	-1119.6	5	5
Age – 41 to 55 years	1226	-1339.9	5	7
Age – Older than 56 years	687	-823.8	5	4
Education – Grade 9 or less	139	-181.2	5	2
Education – Grade 12	629	-705.1	5	6
Education – College	1075	-1153.4	5	6
Education – University	1401	-1492.0	5	8
Gender – Male	1345	-1501.1	5	6
Gender – Female	1909	-2070.5	5	8
Family Income – Under $20,000	248	-299.9	4	5
Family Income – $20,001 to $40,000	614	-680.3	5	6
Family Income – $40,001 to $60,000	714	-745.0	5	6
Family Income – $60,001 to $80,000	540	-598.1	5	3
Family Income – Over $80,000	1044	-1116.9	4	7
With Access to a Vehicle Only	3001	-3306.4	5	8
Car Type – Small	914	-978.6	5	8
Car Type – Medium	931	-1015.9	5	7
Car Type – Large (includes minivans)	751	-829.8	5	7
Car Type – Trucks/SUV's	411	-475.3	4	4

*With 95% confidence

Table 4.10 – Summary of models in vehicle choice model segments

Although some interesting ideas and trends can be drawn from the segments, when the accompanying problems are also considered there does not seem to be any critical information being excluded by building a model based on the entire population. This conclusion is important because it helps rationalize the use of a single set of behavioral parameters in CIMS for all of Canada. More detailed segments and greater attention to demographics would likely continue to increase the explanatory power of the vehicle choice models, and potentially even eliminate some of the counter-intuitive results observed in this section. CIMS operates at a relatively coarse demographic resolution however, and the level of detail that could realistically be included doesn't seem to offer any improvements.

4.3.2 Mode Choice

An almost identical seven segments were developed for the mode choice model following the same utility formulations laid out in equations 4.7 through 4.11, resulting in 28 sub-models. The only differences were that the vehicle access segmentation was replaced with a commuter/non-commuter segmentation, and the vehicle type sub-models were removed. As with the vehicle choice segmentations, each group of sub-models was tested against the base model using a log-likelihood ratio test. The test statistics and results summarized in table 4.11 show that all seven segmentation groups provided an improved understanding of the data with 99% confidence.

Segment	**Sub - Model**	**Test Statistic**	**Degrees of Freedom**	**Reject Null Hypothesis***
Region	5	108.2	40	Yes
City Size	3	48.4	20	Yes
Major Cities	3	185.3	20	Yes
Age	4	217.7	30	Yes
Education	4	73.7	30	Yes
Gender	2	99.3	10	Yes
Income	5	275.1	40	Yes

*Models were significantly different with 99% confidence

Table 4.11 – Significance of mode choice demographic segments

Like the vehicle choice sub-models however, although the base model was highly significant with all signs appearing in the expected direction, the same cannot be said for all of the individual sub-models. Table 4.12 shows how many times each attribute coefficient had the expected sign and was significant over the 28 sub-models. All three time coefficients had the expected signs in all 28 segments, but cost, the number of transfers, and bike route access, had unexpected influences on utility in up to six sub-models. Although bike route access, and the number of transfers could probably have been non-factors for many respondents (especially those who may not have examined the non-vehicle options closely), it is difficult to explain why increasing cost would be seen as a benefit in four of the 28 sub-models. Also of concern is that access to a cycling path was only significant in one sub-model, and pickup/drop-off time, the number of transfers, and the ASC's for SOV, HOV, and transit were significant in less than twenty of the sub-models. This summary information about the mode choice segments shows that they possess a considerable number of weaknesses and although the models may provide some interesting insights, minimal overall value is lost by working with the base model in CIMS.

Coefficient	Times expected sign was observed	Times coefficient was significant*
Cost	24	22
Driving Time	28	27
Pickup/Drop-off Time	28	19
Walking/Waiting Time	28	25
Transfers	24	7
Cycling Path	22	1
ASC – SOV	Na	14
ASC – HOV	Na	9
ASC – Transit	Na	11
ASC - Park n' Ride	Na	25

*With 95% confidence

Table 4.12 Summary of coefficients in mode choice model segments

Table 4.13 illustrates how many coefficients had the expected sign, and how many were statistically significant in each of the mode choice sub-models. The complete sub-model specifications are also available in appendix 7. Some of the most interesting, and reasonable segmentations are those by region, city size, and age, but as with the vehicle choice sub-models, the trends across different sub-models weren't always explainable. For example, all else being equal, park and ride was the least popular mode in all regions, and walking/cycling was the most popular except for Quebec where it was carpooling. The aversion to park and ride could be explained by respondents' general lack of experience with the mode, but Quebecois' attraction to carpooling is strange considering they also had the greatest aversion to high pickup/drop-off times. The importance of driving time was relatively constant across regions, while cost had the highest relative importance in BC and the Atlantic provinces. Although the coefficients in each of the city size sub-models all have the expected signs, there are only negligible differences between the three sub-models, and the base model. There are differences across the age sub-models however, where cost is most important for young and old respondents, possibly because those samples are heavily weighted with students and retirees who have less disposable income, making travel costs a more significant portion of their budget. The attractiveness of the SOV and transit options were relatively similar for all four age groups, but these modes were more attractive than walking/cycling for the elderly, while the reverse was true for the younger age groups, possibly because they were more physically able to undertake more active forms of transportation. Clearly there are a number of estimated differences between the different sub-models, but because so many are either inconsistent, or unexplainable, deciding which ones are valid, and which are artifacts of the smaller sample sizes would be extremely problematic.

Model Segment	**Obs.**	**CLL**	**Expected Signs**	**Significant Coefficients***
All Observations	3,335	-4,088.3	6	9
Region – Atlantic	282	-339.4	5	4
Region – Quebec	758	-909.8	5	5
Region – Ontario	1,277	-1,555.6	6	6
Region – Prairies	597	-723.7	6	5
Region – BC	421	-505.7	6	7
City Size – More than 1,000,000	1,707	-2,070.6	6	6
City Size – 500,000 to 1,000,000	944	-1,151.2	6	5
City Size – Less than 500,000	684	-842.3	6	6
City – Toronto	750	-900.4	6	6
City – Vancouver	361	-435.7	6	6
City – Montreal	596	-709.1	4	5
Age – Younger than 25 years	300	-322.9	6	6
Age – 26 to 40 years	1,074	-1,318.2	6	6
Age – 41 to 55 years	1,254	-1,466.2	6	7
Age – Older than 56 years	701	-865.1	5	5
Education – Grade 9 or less	134	-162.4	3	0
Education – Grade 12	649	-790.4	5	7
Education – College	1,094	-1,334.8	6	4
Education – University	1,432	-1,732.3	6	7
Gender – Male	1,366	-1,671.3	6	9
Gender – Female	1,951	-2,345.6	5	6
Family Income – Under $20,000	253	-308.6	4	3
Family Income – $20,001 to $40,000	626	-737.7	4	4
Family Income – $40,001 to $60,000	727	-921.0	6	5
Family Income – $60,001 to $80,000	547	-642.1	6	6
Family Income – Over $80,000	1,058	-1,194.5	6	7
Commuters Only	2,637	-3,146.9	6	8

*With 95% confidence

Table 4.13 Summary of models in mode choice model segments

4.4 Accounting for Uncertainty

Until now only the maximum likelihood estimates have been presented, and although they do provide the best explanation of the data, they don't provide a perfect explanation. Many other combinations of β parameters could provide reasonable fits with the observed choices, and by just focusing on the maximum likelihood estimators these additional possibilities are ignored. Accounting for these alternative parameter estimates allows the full range of possible outcomes and their associated probabilities of occurrence to be assessed. Once this information is available, the relative strength (or certainty) of the MLE's can be easily seen. If many parameter combinations are equally likely, the confidence in the MLE's should be reduced, but if the MLE's are much more likely than the alternative combinations, confidence in them should be increased. These two extremes are illustrated in figures 4.24 and 4.25, where both diagrams show the probability that various parameter estimates explain hypothetical data sets. In both cases, the maximum likelihood estimator is identical (5), but the certainty in that estimate is much greater in figure 4.25.

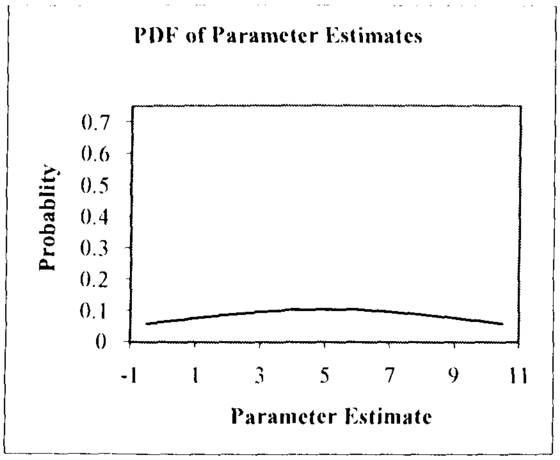

Figure 4.24 – Diffuse pdf for hypothetical parameter

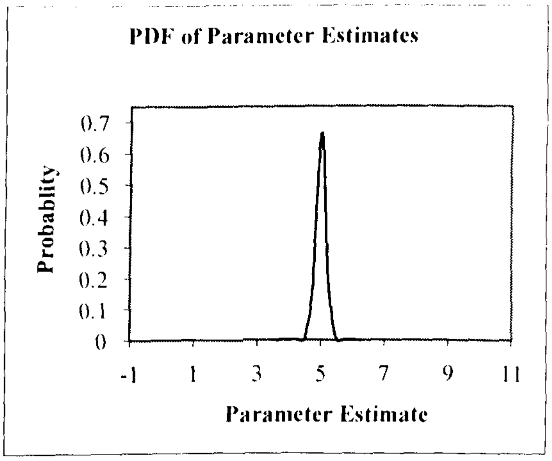

Figure 4.25 – Narrow pdf for hypothetical parameter

This way of thinking about uncertainty is significantly different from confidence intervals or sensitivity analyses that focus primarily on the potential outcomes, without considering their probability of their occurrence. Without both types of information, it is impossible to take advantage of the full benefits of uncertainty analysis. Morgan and Henrion (1990) outline three general reasons why incorporating uncertainty is often beneficial to policy analysis. First, accounting for uncertainty allows the most important factors in a decision to be identified, and potentially unexpected outcomes can be anticipated. Second, disagreements over predicted outcomes can be debated more fruitfully by comparing full ranges of potential outcomes (which may overlap) instead of focusing on single point estimates. In highly uncertain analysis, this can be particularly useful, because estimates that initially seem to be vastly different may in fact overlap with each other once uncertainty is accounted for. Third, properly documenting the uncertainty in an analysis helps future work return to the ideas and incorporate them into additional analysis without misinterpreting or overextending the results. These three reasons in combination with the intuitive notion that attempts to understand human behavior will always be clouded with uncertainty give a strong justification for the following techniques for quantifying uncertainty in discrete choice models.

4.4.1 Technique for Quantifying Uncertainty in Discrete Choice Models

In order to account for the uncertainty in the β parameters of the vehicle and mode choice models developed in section 4.2, it is necessary to return to the cumulative log likelihood function presented in equation 4.2. The estimation routine in LIMDEP 7.0 focuses exclusively on finding the parameters that maximize this equation using the most efficient method possible. This is accomplished with the first and second order derivatives of the likelihood function, and as a result of the efficient solving algorithm, many of the possible combinations of beta parameters are skipped over in the search for the MLE. The approach taken in this section first develops a series of possible values for each β parameter centered at its respective MLE, and then determines the value of the likelihood function for every possible combination of β parameters. The value of the likelihood function for any set of parameters is directly proportional to the probability of that combination of parameters occurring, so once enough combinations are evaluated, the complete joint probability density function can be interpolated. Fortunately, local minimum and maximums are not a concern because the parameter space of the log-likelihood function for an MNL model is concave in all parameters (Train, 2003), and as such, the likelihood function will decrease as any of the parameters are moved in either direction away from the MLE. This technique is illustrated for a hypothetical DCM with a single β parameter in the figure 4.26. The left hand side of the diagram shows the likelihood function evaluated at nine different parameter values. These points are then scaled to unity on the right hand side and interpolated to form a probability density function for the full range of explored β values. Although much harder to visualize, the technique is the same when dealing with a multi-dimensional parameter space.

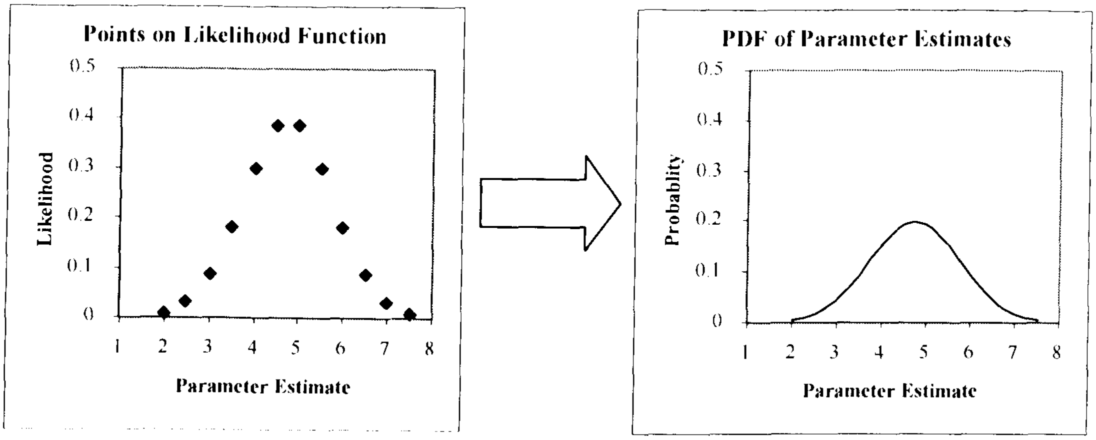

Figure 4.26 Transforming likelihood values to a probability distribution function

Uncertainty was explored in eight of nine vehicle choice parameters, and nine of eleven mode choice parameters. In both models, the alternative specific constants set to zero in the initial estimation (hydrogen fuel cell vehicles, and walking/cycling) were fixed at zero for the uncertainty analysis. Fixing one of the alternative specific constants to its maximum likelihood estimator does not detract from the analysis because it is only the difference in utility values that matter, so if one is arbitrarily fixed to zero the full range of possible differences is still explored. Because of computational time limitations, the park & ride alternative specific constant was also fixed to its MLE (-1.95) to reduce the amount of uncertainty being considered in the mode choice model. This simplification is of minor significance because the park and ride option is not included in CIMS, so the uncertainty surrounding its utility constant is relatively unimportant.

Series of seven possible parameter estimates were centered around each of the uncertain β parameters' MLE's so that the marginal probability for the values furthest from the

MLE's were between 2% and 5%[20]. The marginal probability of a parameter value is its probability of occurring independent of the other parameters' values, so this step means that between 4% and 10% of the possible values for each parameter are not being considered. The resulting ranges of parameter values for the vehicle and mode choice models are shown in tables 4.14 and 4.15 respectively. The log-likelihood function for every possible combination of these β parameters was then calculated with the 3,278, and 3,335 choice observations using macros programmed in Excel 2000. Ideally, a wider range of values, and finer intervals could have been explored, but the computation time required to run the Excel macros was already considerable, and the fact that the likelihood functions are concave minimized the potential to overlook subtle behavior.

Attribute	**Low Value**	**High Value**
Capital Cost	-5E-05	-0.0001
Fuel Cost	-0.002	-0.007
Fuel Availability	0.9845	1.3411
Express Lane Access	-0.043	-0.277
Power	-0.103	-0.337
Gasoline Vehicle ASC	-1.549	-1.843
Alternative Fuel Vehicle ASC	-1.805	-2.206
Hybrid-Electric Vehicle ASC	-0.267	-0.462
Hydrogen Fuel Cell Vehicle ASC	0	0

Table 4.14 Range of values explored in the vehicle choice uncertainty analysis.

Attribute	**Low Value**	**High Value**
Commuting Cost	-0.051	-0.038
Traveling Time	-0.086	-0.060
Walk/Wait Time	-0.093	-0.066
Pickup/Drop-off Time	-0.326	0.008
Number of Transfers	-0.004	-0.001
Cycling Route Access	-0.069	0.416
Single Occupancy Vehicle ASC	-0.666	-0.399
High Occupancy Vehicle ASC	-0.591	-0.355
Transit ASC	-0.601	-0.324
Park & Ride ASC	-1.947	-1.947
Walk/Cycle ASC	0	0

Table 4.15 Range of values explored in the mode choice uncertainty analysis.

[20] This step was somewhat problematic because the ranges were determined using subsets of uncertain parameters. Because the marginals are dependant on all the uncertain parameters, once the full set was analyzed, the desired marginal wasn't achieved exactly.

4.4.2 Results of the Uncertainty Analysis

Figures 4.27 through 4.34 present the marginal probability distributions for each of the uncertain parameters in the vehicle choice models. So that the different figures can be effectively compared, the vertical scales range from 0% to 30%. Horizontally, the scales have been chosen so that they reflect each attribute's average contribution to utility. For example, the range for the capital cost coefficient is much smaller than the range for any of the alternative specific constants because its contribution to utility is multiplied by the values for capital cost. If these scaling adjustments were not made, the distributions for the parameters that are multiplied by larger numbers would appear to be very narrow (highly certain), which would misrepresent the actual uncertainty because utility is the measure of interest. Using the presentation format in the following figures, direct visual comparisons can be made, where high, narrow marginals indicate little uncertainty in the parameter's contribution to utility, and short, wide marginals indicate the opposite.

The probability distribution functions provide additional information that is not available from the t-statistics presented in section 4.2. For example, even though both β_{FC}, and β_{EXP} have very similar t-statistics (~3), the uncertainty in those parameters is quite different, with β_{FC}'s contribution to utility being almost three times as uncertain. An additional point of interest is that although β_{CC} and β_{FC} contribute the most uncertainty to utility, the actual values they are likely to cover fall within relatively small ranges. For example, 95% of the likely β_{CC} values are between $-1.22*10^{-4}$ and $-5.86*10^{-5}$. This finding is important because the relationship between these parameters is typically used to estimate private discount rates (see section 5.3), so a narrow range of likely parameter values will translate to a narrow range of likely discount rate estimates.

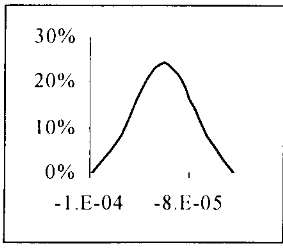

Figure 4.27 – pdf β_{CC}

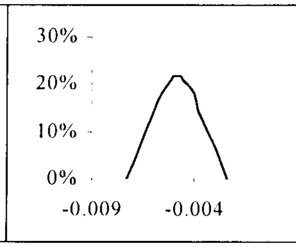

Figure 4.28 – pdf β_{FC}

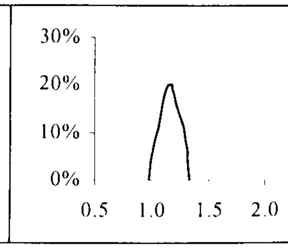

Figure 4.29 – pdf β_{FA}

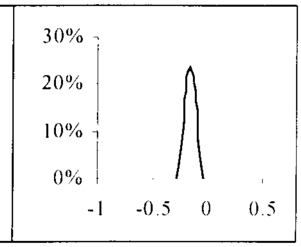

Figure 4.30 – pdf β_{EXP}

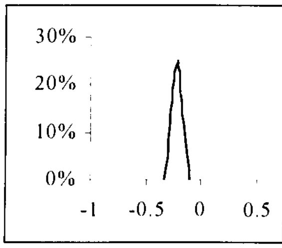

Figure 4.31 – pdf β_{POW}

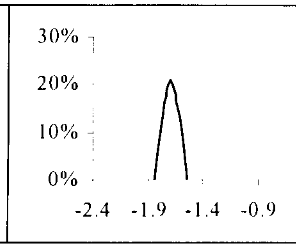

Figure 4.32 – pdf β_{GAS}

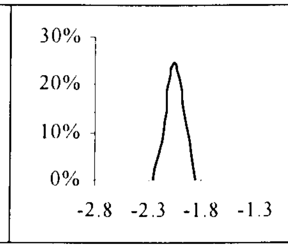

Figure 4.33 – pdf β_{AFT}

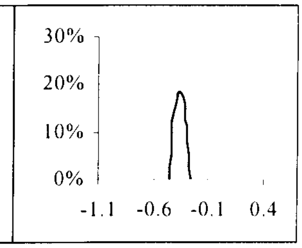

Figure 4.34 – pdf β_{HET}

Figures 4.35 through 4.43 present the marginal probability distribution functions for the beta parameters in the mode choice model and, similarly to the vehicle choice figures, the vertical scales all range from 0% to 40%, and the horizontal ranges are selected to be directly comparable in terms of contribution to utility. In terms of the relative contributions to utility, these figures illustrate that the three time variables are the least uncertain parameters. This finding is important because as discussed in section 4.2, they are also the most influential variables on choice predictions. Also of note is the relatively large degree of uncertainty surrounding the utility contributions from $\beta_{Transfers}$ and $\beta_{CyclePath}$, both of which have a significant probability of actually subtracting from a mode's utility. These possibilities match with the t-statistics presented in table 4.6, which showed that both of these parameters couldn't be significantly differentiated from zero.

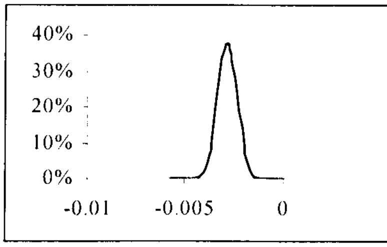

Figure 4.35 – pdf β_{Cost}

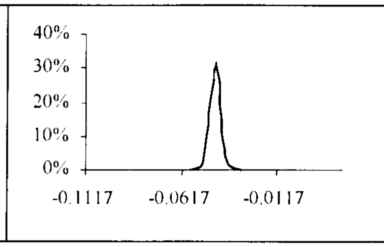

Figure 4.36 – pdf β_{DT}

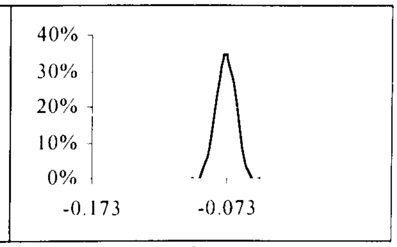

Figure 4.37 – pdf β_{WWT}

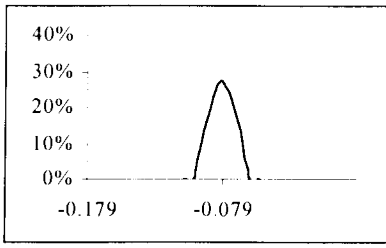

Figure 4.38 – pdf β_{PDT}

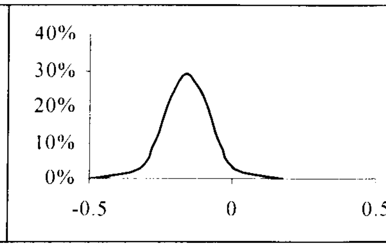

Figure 4.39 – pdf $\beta_{Transfers}$

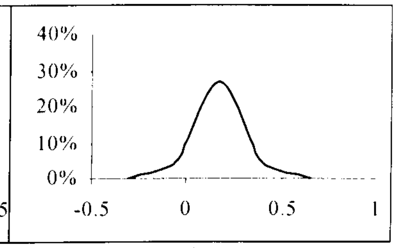

Figure 4.40 – pdf $\beta_{CyclePath}$

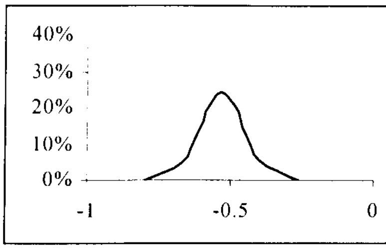

Figure 4.41 – pdf β_{SOV}

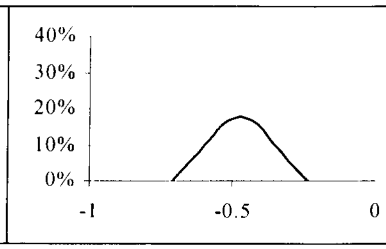

Figure 4.42 – pdf β_{HOV}

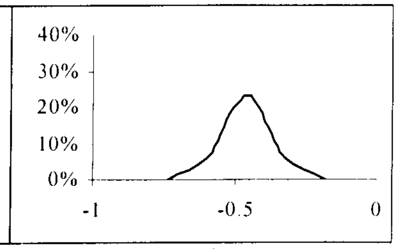

Figure 4.43 – pdf $\beta_{Transit}$

In addition to the marginal probability distributions for each of the uncertain parameters, vehicle type market shares were calculated for each combination of parameter values. Figures 4.44 through 4.47 show market share distributions for the different vehicle types in a scenario where the attributes reflect current values, and cases where each of the three non-gasoline vehicle types are individually promoted through cost subsidization, and increased fuel availability (the details of these scenarios are available in appendix 4). As with the marginal probability distributions, the peak of each curve represents the maximum likelihood prediction for that vehicle type's market share, and the wider the distribution the less certain the prediction. In all of the scenarios, the figures show a range of possible market shares for each of the vehicle types, where the most likely estimate is sometimes less than 20% probable. Possible values for vehicle type market shares cover ranges of up to 20%, and often overlap, which provides backing to the idea that the single most likely outcomes shouldn't be focused on.

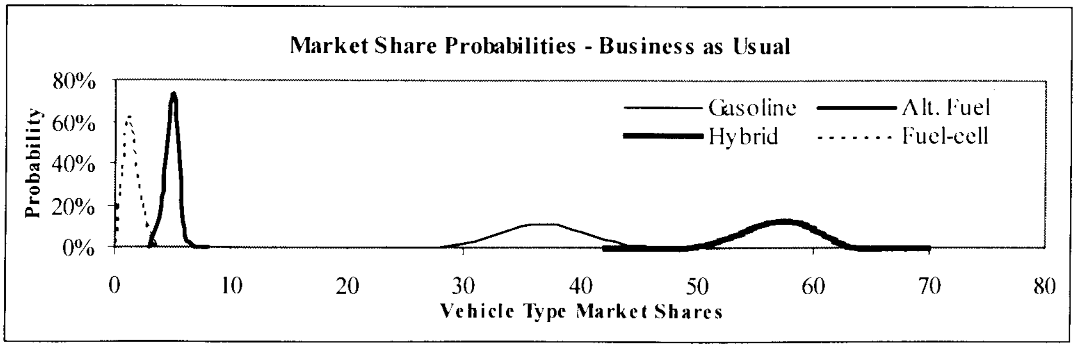

Figure 4.44 – MS probabilities - Business as usual

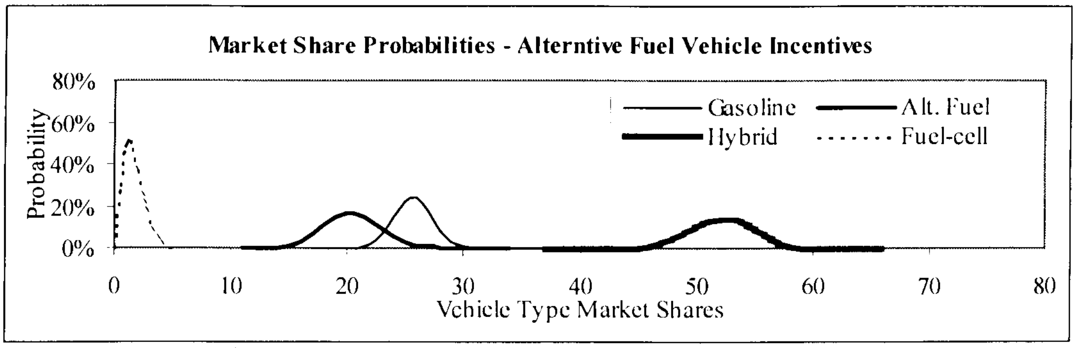

Figure 4.45 – MS probabilities - Pro AFV policy

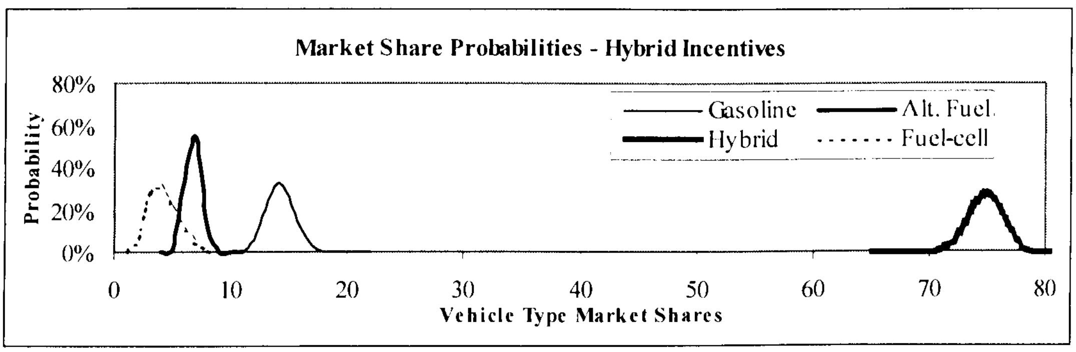

Figure 4.46 – MS probabilities - Pro hybrid policy

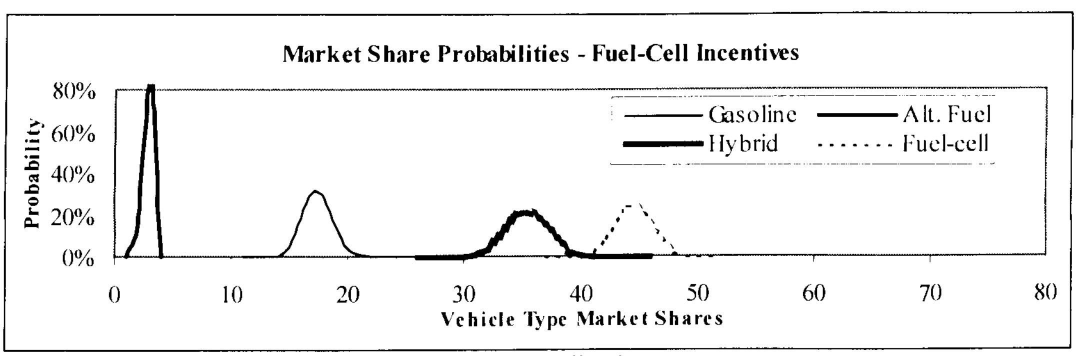

Figure 4.47 – MS probabilities – Pro hydrogen fuel cell policy

Figures 4.48 through 4.51 show the market share distributions for the different commuting modes in a business as usual scenario, and scenarios where each of the non-SOV options are each individually promoted (the details of these scenarios are available in appendix 5). The widths of the distributions are slightly narrower than those obtained for the different vehicle types, with ranges of up to 15% possible. The narrower distributions are partially explained because fewer possible values were explored in some parameters, which has the effect of increasing the likelihood of the maximum likelihood estimates relative to the less likely parameter values. In general, both the vehicle type and mode type market share distributions are narrow considering the range of values that seemed likely in each of the parameters' marginal probability distributions. This is encouraging, because although the importance of each attribute is uncertain, that uncertainty is not additive, and the resulting uncertainty surrounding the market shares (and costs, and emissions) is not overwhelming. The techniques in this section have successfully demonstrated the degree of uncertainty in the vehicle and mode choice models, and ways of incorporating this understanding into CIMS will be discussed in section 5.5.

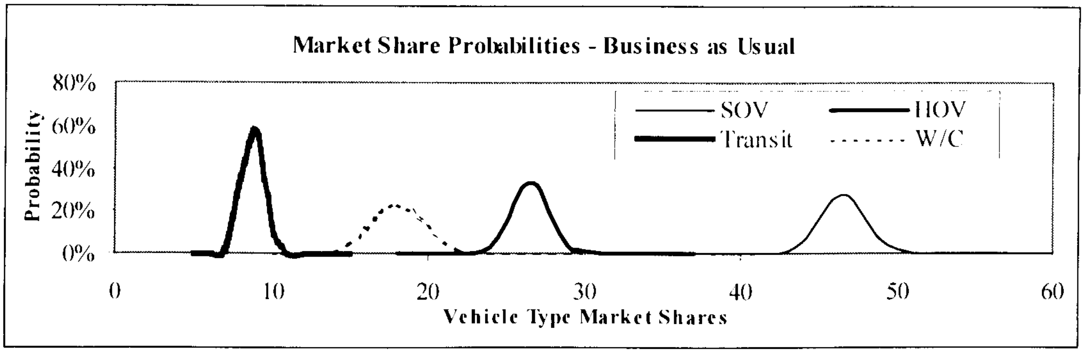

Figure 4.48 MS frequencies - Business as usual

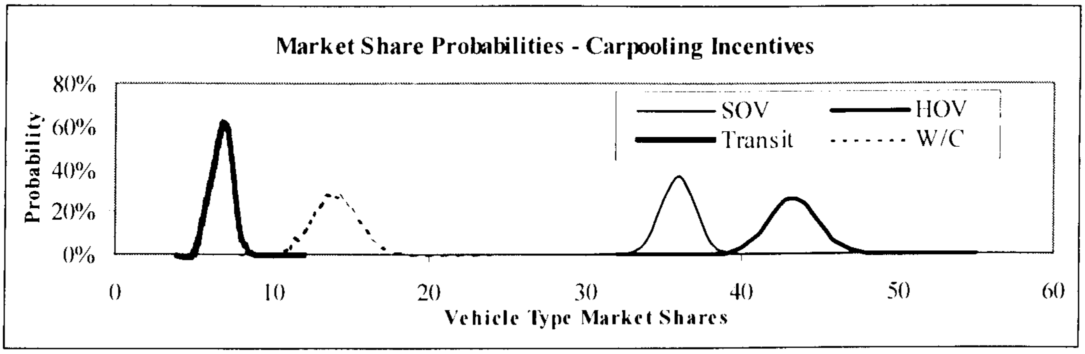

Figure 4.49 MS frequencies - Pro carpooling policy

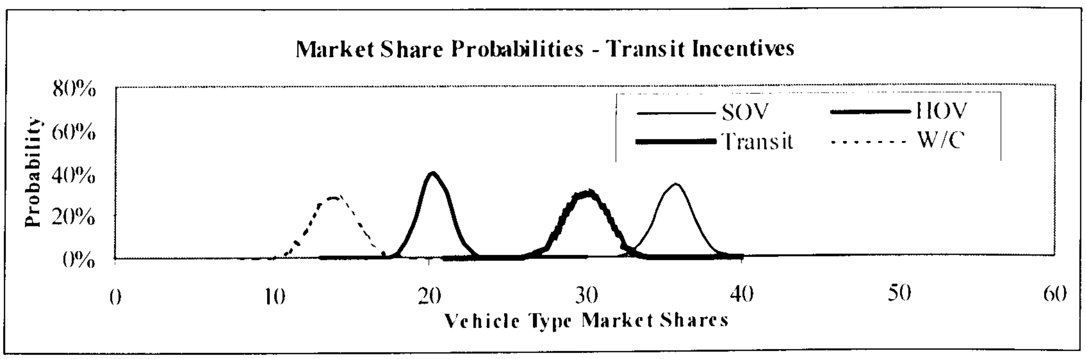

Figure 4.50 MS frequencies - Pro transit policy

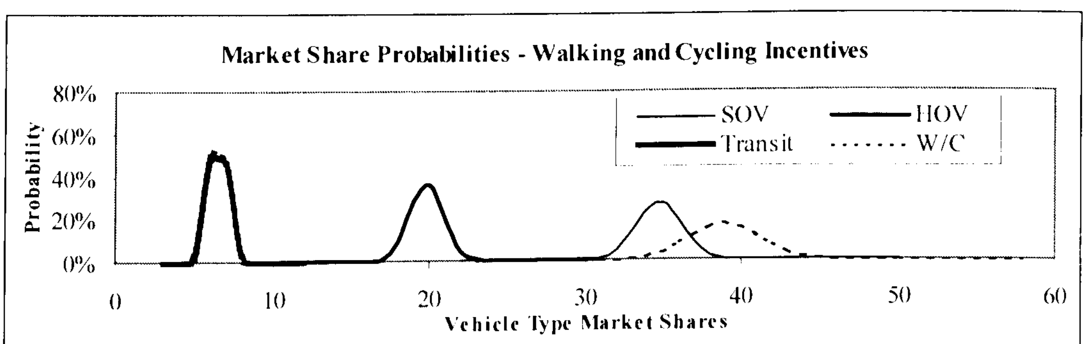

Figure 4.51 MS frequencies - Pro walk/cycle policy

5 INCORPORATING DCM'S INTO CIMS

The discrete choice models developed in section 4.2 are effective at predicting market shares for mode and vehicle choice in isolation, but because they are isolated from the rest of the economy, they are not immediately useful in an energy-economy modeling context. To gain value from the discrete choice models, their performance will be incorporated into CIMS once two specific obstacles are overcome. First, the technologies themselves, and their organization in the DCM's do not match exactly with the technology hierarchy used in CIMS. Second, the key CIMS parameters (v, i, and r) don't correspond directly with the weighting parameters used in discrete choice models. The remainder of this section elaborates on these issues, and discusses the techniques used to match the DCM technologies and predictive characteristics to CIMS (sections 5.1 through 5.3). The resulting CIMS parameters, and means of propagating estimates of uncertainty into CIMS are discussed in sections 5.4 and 5.5 respectively.

5.1 Matching the Mode Choice DCM to CIMS

Two specific problems were encountered when matching the discrete choice model for mode choice to CIMS. The first of these is that CIMS competes SOV's, HOV's, transit, and walking/cycling, whereas the DCM also includes a park and ride option. This issue is easily resolved by removing the park and ride option from the DCM, and leaving the other utility formulations unchanged. This action doesn't necessitate alterations to the utility formulations because of the multinomial-logit model's property of independent choice probabilities (see section 2.2). By removing the park and ride mode, the market share it would have received is divided between the remaining modes so that their relative choice probabilities are unchanged. This step also makes sense intuitively, because a person who would have chosen the park and ride option was already willing to use a mixture of modes, so their choices in the absence of the park and ride option seem likely to also comprise a mixture of modes.

The second problem is that CIMS competes modes using capital cost as an attribute, which wasn't included in the DCM formulation. Capital costs are commonly excluded from mode choice models (Washbrook, 2000 and Bhat, 1997), because the decision is viewed as a day-to-day usage decision where the sunk capital costs of a vehicle purchase do not influence the decision. In other words, once a person has purchased a vehicle, only the marginal cost of operating that vehicle influence the decision to use it[21]. The reason that not including capital costs in the DCM formulation is a problem stems from the way modes are competed in CIMS. Figure 5.1 presents a simplified illustration of the mode choice competition in CIMS[22], where light grey boxes are individual technologies, and dark grey boxes are the parent nodes that group competing technologies or nodes together. When a competition occurs between technologies (vehicle 1 and vehicle 2 for example), the characteristics of those technologies are used to determine the resulting market shares. When a competition occurs between nodes (SOV, HOV, transit, and walking/cycling for example), market shares are determined using the market share weighted averages of the life cycle costs for the underlying technologies. In the mode choice competition for example, the SOV and HOV characteristics are both based on the market shares and life cycle costs of vehicle one and two.

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[21] The decision to model mode choice as a usage or purchasing decision has implications for the calculation of costs, because it is important to know if people who change their commuting patterns also change their vehicle ownership. For example, does a commuter who decides to start taking transit to work also decide to sell their vehicle. This issue is returned to in more detail in section 6.

[22] In reality, the underlying vehicle technologies are developed in much greater detail.

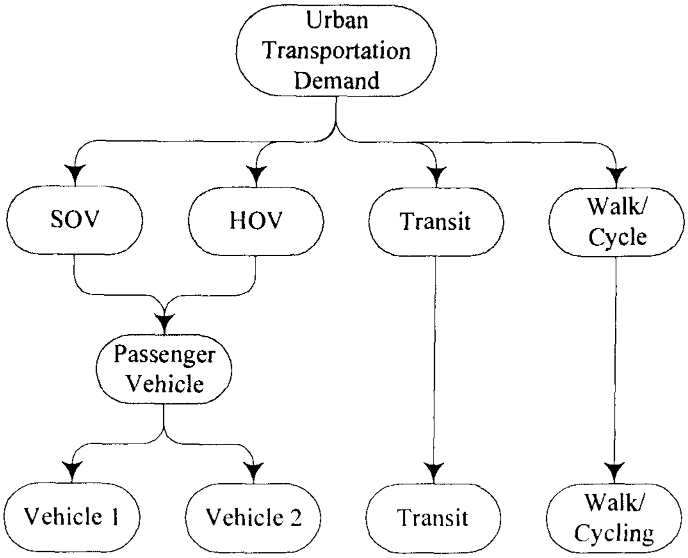

Figure 5.1 – Simplified urban transportation technology hierarchy in CIMS

This method of calculating market shares for mode choice in CIMS leads to a problem because the capital costs, which are needed in the vehicle choice competition, cannot be excluded from the mode choice competition where they are not desired. CIMS does not currently possess the capability to exclude or block capital costs from market share calculations, so to circumvent the problem, the mode choice competition is determined outside the simulation. More specifically, CIMS is run normally without any changes to the mode choice parameters, and once complete, the weighted average characteristics of the resulting vehicle mix are calculated in an Excel spreadsheet. This allows the capital costs to be omitted, and the remaining parameters are used in the external mode choice competition. The resulting mode shares are used to determine the total stock in each mode's underlying technologies, so that costs and emissions can be calculated.

Although this approach fails to directly embed the performance of the discrete choice model within CIMS, the predictions are almost identical[23] because the technology attributes (excluding capital costs) are obtained from the simulation output, and the mode shares are calculated using the parameters that would have been embedded in CIMS. Macro economic feedbacks have been turned off in all simulations to prevent mode

[23] Slight discrepancies will occur because the CIMS outputs that the external mode choice calculation is based on are less precise than the values actually used in CIMS' calculations.

shares from affecting fuel costs, which would in turn affect vehicle stocks. If this feedback were allowed to occur, market shares calculated outside the model wouldn't be correct because equilibrium would not have been reached. In reality, any errors introduced by disabling the macro-economic feedbacks are likely minimal because the demand for transportation services is typically inelastic (Espey, 1997). In future, the revised competition algorithm could be directly embedded in CIMS so that macro features could be activated, and all competition and costing calculations could occur within the model. This could be simply accomplished by keeping the components of the vehicle type life cycle costs disaggregated when passing them to the mode choice competition. CIMS users would also need to be given controls to declare which components of the life cycle cost should passed to the mode choice competition. These steps would allow users to prevent capital costs from influencing the mode choice competition, without removing them from the vehicle choice competitions.

5.2 Matching the Vehicle Choice DCM to CIMS

The challenges encountered when preparing the vehicle choice model for integration with CIMS were considerably more complex than those linked to the mode choice model. In total, four specific problems were addressed, two of which stem from the fact that CIMS provides a more detailed breakdown of fuel and engine types than presented in the survey questions. Instead of reducing the complexity of the DCM as was the case in the mode choice model, the DCM needs to be expanded to represent a wider variety of decisions. CIMS' complete model for vehicle choice is presented in figure 5.2, where the clear boxes are individual technologies, and light and dark grey boxes group together competing technologies or nodes. The underlying (or child) technologies/nodes of light grey boxes compete endogenously within CIMS, while those stemming from dark grey boxes are currently assigned market share using exogenously defined fixed ratios.

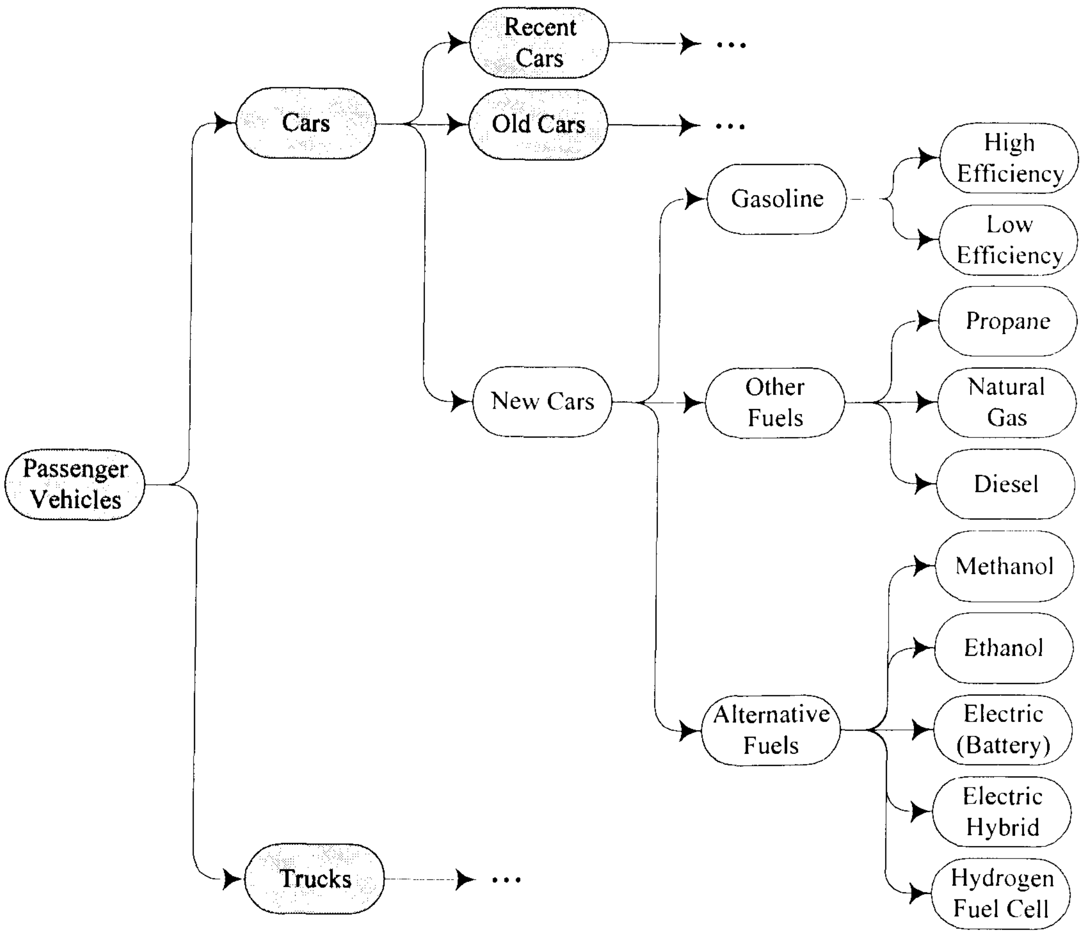

Figure 5.2 Vehicle choice technology hierarchy in CIMS

The first problem presented by figure 5.2 is that the nested node structure for various vehicle types results in some undesired substitution patterns. For example, if all ten vehicle types had identical characteristics, one would expect them to each obtain equal market shares, but this is not the case, with the desired and actual predictions presented in table 5.1. The reason for the discrepancies is that the weighted average costs used to compete the alternative fuels, other fuels, and gasoline vehicles nodes would be equal, so these nodes are first assigned equal market shares (33%). CIMS would then divide the 33% equally between the competing child technologies, and because the number of technologies in each node is different, the resulting market shares will also be different. This is an extreme example, but the same sorts of problems occur regardless of the technology characteristics. These substitution patterns are difficult to defend theoretically[24], and they make it very difficult to match CIMS to the performance of the DCM that doesn't contain any nested competitions. To solve the problem, all ten of the new car technologies were reassigned to the gasoline vehicles node, and the market share for that node was fixed at 100%. An identical operation was performed on the new trucks node. These modifications have been made to the version of CIMS used for this research, but in order to make CIMS as transparent and intuitive as possible, it is strongly recommended that they be adopted permanently.

Technology	Market Share	
	Desired Prediction	CIMS Prediction
High Efficiency Gas	10%	17%
Low Efficiency Gas	10%	17%
Propane	10%	11%
Natural Gas	10%	11%
Diesel	10%	11%
Methanol	10%	7%
Ethanol	10%	7%
Electric (Battery)	10%	7%
Hybrid-Electric	10%	7%
Hydrogen Fuel Cell	10%	7%

Table 5.1 – Market share discrepancies resulting from nested technology structure

The second problem presented by the vehicle choice models is that the four technologies in the discrete choice model don't match the ten modeled in CIMS. As with the mode choice model, this problem can be solved because the IIA property of the multinomial logit model permits the addition or subtraction of alternatives without the need to re-estimate the model. This step was accomplished by mapping the DCM technologies directly to CIMS where possible, and adding new technologies where necessary. All new technologies had the same weighting coefficients for attributes, but the alternative specific constants were chosen to reflect differences in vehicle types where appropriate. Hybrid electric and hydrogen fuel cell vehicles were mapped directly to their namesakes in CIMS, and the alternative fuel vehicle was assumed to be equivalent to propane, natural gas, methanol, and ethanol options, so no changes to the alternative specific

[24] They were initially grouped this way because CIMS did not allow more than five technologies at a node, and the hierarchy allowed policies like vehicle emissions standards to be roughly simulated. The technology limitation no longer exists, and these types of policies can be simulated using other techniques.

constants were required for these technologies. The ASC for diesel vehicles was set as the average of gasoline and alternative fuel vehicles, indicating that it was slightly less preferred than the gasoline option, but more so than less conventional automotive fuels. The ASC's for the high and low efficiency gasoline vehicles were selected so that the DCM market shares were equivalent to the business as usual shares predicted in CIMS, and that the market share weighted average of their alternative specific constants equaled the ASC of the gasoline vehicle in the base DCM. Selecting an ASC for electric vehicles was somewhat problematic because the driving range, and recharging time are both significant attributes for this type of vehicle (Bunch, 1993) that weren't tested in this vehicle choice experiment. Based on the work of Ewing (2000), and assuming a driving range of 160 km, and a recharging time of 40 minutes, 0.54 was subtracted from the alternative specific constant of the hydrogen fuel cell vehicle's ASC. The resulting alternative specific constants displayed in table 5.2, were input into the version of CIMS used for this research, and should be included in the standard version in the future. It is important to note that although a number of technologies in CIMS are taking on the same DCM attribute coefficients and ASC's (all of the alternative fuel vehicles for example), they won't necessarily have identical costs within CIMS, because the tangible and intangible attribute values can still be set independently.

Vehicle Type	**Alternative Specific Constant**
Methanol	-2.01
Ethanol	-2.01
Electric	-0.54
Hybrid-electric	-0.36
Hydrogen Fuel Cell	0.00
Diesel	-1.86
Propane	-2.01
Natural Gas	-2.01
Gas – High Efficiency	-2.39
Gas – Low Efficiency	-0.92

Table 5.2 – Alternative specific constants for CIMS' vehicle types.

After the technology hierarchy had been modified to match with CIMS, the vehicle choice models also needed to be adjusted to account for the possible false environmental effect mentioned in section 4.2. The concern with emissions reductions is that people may unconsciously say they are willing to pay more for them than they would do so in reality, so the alternative specific constants would be artificially inflated to reflect the survey responses. To account for this problem, a portion of each vehicle type's alternative specific constant was assumed to represent its environmental attractiveness, and that portion was removed. The amount subtracted was based on the work of Ewing (2000), who analyzed the influence of emissions reductions as a varying attribute. In order to be able to use the information from Ewing's model, all of the coefficients in his model were scaled so that the coefficient for capital cost equaled the value for capital cost obtained in this research. Next, the scaled estimate for the emissions reduction coefficient was multiplied by the percentage emissions reductions for each vehicle type to produce an emissions modifier for each vehicle type's alternative specific constant. The resulting modifiers are presented in table 5.3. It is important to note that the influence of reduced emissions on utility could be real, so the policy analysis performed in section 6 is undertaken with and without the environmental effect.

Vehicle Type	**Emissions Modifier**
Methanol	-0.18
Ethanol	-0.04
Electric	0.00
Hybrid-electric	-0.09
Hydrogen Fuel Cell	0.00
Natural Gas	-0.16
Propane	-0.19
Diesel	-0.16
Gas – High Efficiency	-0.11
Gas – Low Efficiency	-0.32

Table 5.3 – Alternative Specific Constant Modifiers for Emissions Effect

The final challenge presented by the vehicle choice models was that the DCM's don't account for the availability of different makes and models within a vehicle type. For example, even though a hydrogen fuel cell car may be preferable to a comparable gasoline vehicle, if 100 different makes of gasoline vehicles are available compared to one make of hydrogen fuel cell vehicle, the gasoline vehicles will likely capture a greater cumulative share of the market. To account for this effect, an additional factor has been added to each vehicle type's alternative specific constant to represent its availability, assuming that the base model represents a scenario where all vehicle types are equally available. Similar to the possible emissions modifiers, these modifiers are highly speculative because they were not part of the initial experimental design, and as such, the policy simulations in section 6 are carried out both with and without the modifiers. The modifiers were initially calculated by determining the necessary adjustments to the base alternative specific constants so that the resulting market shares were equivalent to those presented in table 5.4. These target market shares were based on CIMS' business as usual predictions before any modifications to the decision algorithms were made. The same table also shows the alternative specific constant modifiers needed to achieve those market shares. Appendix 8 contains additional tables of alternative specific constant modifiers that are designed to reflect different availability scenarios. These are unfortunately not dynamic, because only one set of modifiers can be used for a single CIMS run (see section 5.3), but they do provide additional flexibility that wasn't previously available in CIMS.

Vehicle Type	**Market Share**	**Availability Modifier**
Methanol	0%	-1.44
Ethanol	1%	0.94
Electric	0%	-2.67
Hybrid-electric	1%	-5.36
Hydrogen Fuel Cell	0%	0.00
Propane	0%	-0.48
Diesel	4%	1.94
Natural Gas	1%	1.31
Gas – High Efficiency	49%	3.10
Gas – Low Efficiency	44%	2.26

Table 5.4 – Vehicle Type Market Shares, and Associated Availability Modifiers

Although make and model availability is undoubtedly an important component of vehicle choice, the results of this exercise show that some other effects are probably present because the sizes of the modifiers are not consistent. For example, the electric hybrid modifier is much larger than the hydrogen fuel cell vehicle modifier even though some hybrid cars exist, while no hydrogen fuel cell vehicles can be purchased yet. As a result, these modifiers are recommended only for use as a sensitivity analysis in combination with the base estimates. This approach is motivated in part by DeCanio and Laitner (1997), where techniques that solely use the calibrated estimates are critiqued for being too static in their predictions because the calibration is trying to account for too many different factors.

In future, it is recommended that availability be modeled more explicitly so that it can be easily changed to reflect different scenarios. Two possible approaches to this challenge are discussed here in hopes that they will be addressed more thoroughly in future research. First, the CIMS vehicle choice algorithm could be split into a number of identical competitions designed to reflect the different classes of cars people focus their vehicle searches within (small cars and SUV's for example). Within each of these sub-decisions, CIMS would be modified to allow the analyst to declare which vehicle types are available (hybrids not being available in the SUV decision for example). This approach would reflect consumer's apparent willingness to purchase alternative vehicle technologies as long as they are available in the vehicle type of interest. A second approach would be to repeat the vehicle choice survey with an additional attribute describing the number of models available in each vehicle type. The model could then be estimated with availability explicitly defined as an attribute, and the market dynamics would be endogenous to the model. A challenge with this approach is that describing availability in a hypothetical choice is extremely difficult, and would present a significant hurdle in survey design to ensure respondents could picture the intended market scenario.

5.3 Estimating CIMS Parameters

Once the performance and structure of the discrete choice models had been suitably modified to reflect the desired mode and vehicle choice decisions being modeled in CIMS, their behavioral performance could be incorporated into CIMS. Equation 5.1 (initially introduced as equation 1.2) illustrates how market share for competing technologies is allocated in CIMS.

$$MS_j = \frac{\left[CC_j \times \frac{r}{1-(1+r)^{-n}} + MC_j + EC_j + i_j\right]^{-v}}{\sum_{k=1}^{K}\left\{\left[CC_k \times \frac{r}{1-(1+r)^{-n}} + MC_k + EC_k + i_k\right]^{-v}\right\}} \qquad \textit{(Equation 5.1)}$$

In the equation, MS_j is the market share of technology j, CC_j is the capital cost, r is the discount rate, n is the technology lifespan, MC_j is the maintenance cost, EC_j are the energy costs, i_j is the intangible cost, v describes the degree of market heterogeneity, and K is the number of competing technologies. Two key differences exist between this equation and the market share calculation for discrete choice models (equation 2.6), each of which present challenges for matching the two together. First, the i parameter in CIMS is a single constant, whereas in the DCM's the non-monetary attributes are each explicitly defined, and weighted by their own coefficients. As a result, the same amount of detail and flexibility that is present in a DCM can't be expressed in CIMS using the current algorithm. Second, the observed utility is the exponent of the term for each alternative in the DCM, whereas in CIMS, the life cycle cost is the exponential base in each term. Although both relationships produce exponential curves, this difference means that changes in market share for the DCM's are dictated by the magnitude of the differences between utility, while in CIMS, changes in market share are dictated by the ratio of life cycle costs. This difference in the performance of the two relationships makes it impossible to make the two curves equivalent, and as discussed at the end of this section, it also has implications for market share calculations and cost estimates for nested nodes.

Two basic approaches exist for bridging these disconnects between the DCM's and CIMS' market share allocation algorithms. First, it is possible to maintain the existing algorithms within CIMS, and select the v, i, and, r parameters so that the predictions in CIMS match those produced by the DCM's. Alternatively, the market share allocation algorithms in CIMS could be replaced with the market share allocation formula for DCM's directly. The first approach is the simplest, because it doesn't necessitate any structural changes to CIMS, but at the same time it reduces modeling flexibility because intangibles can't be manipulated individually or dynamically, a perfect match with DCM predictions isn't possible, and estimating parameter values is still subject to a degree of arbitrariness. The second approach would make the internal workings of CIMS more complex (especially during a changeover from one methodology to another), but flexibility would be maximized, and the performance of the DCM's would be perfectly preserved. These tradeoffs were discussed at length within EMRG (Horne and Rivers, 2002), and the decision was made to follow the first approach, primarily because of the desire to preserve simplicity and consistency across the model. If more competition nodes are based on discrete choice models, this decision deserves revisiting.

The first approach is possible because in general, the market share curves for CIMS and DCM's are essentially mirror images of each other, as illustrated for a two technology case in figures 5.3 and 5.4. Although CIMS allocates market share based on life cycle costs[25], while DCM's allocate based on utility, the mathematical forms for market share result in similar behavior. For a given change in cost or utility, each model predicts significant market share changes (high elasticities) when a technology has close to 50% market share (the dark squares on either figure). Conversely, when a technology has the majority or minority of market share, both models predict small changes in market share (low elasticity) for the same change in cost or utility (the light triangles on either figure). The techniques described in the following paragraphs describe a standardized methodology for mapping the β parameters in DCM's to the v, i, and r parameters in CIMS that make the market share predictions as equivalent as possible.

[25] As mentioned, the life cycle costs in CIMS contain financial and non-financial costs, so they are analogous to utility in many ways.

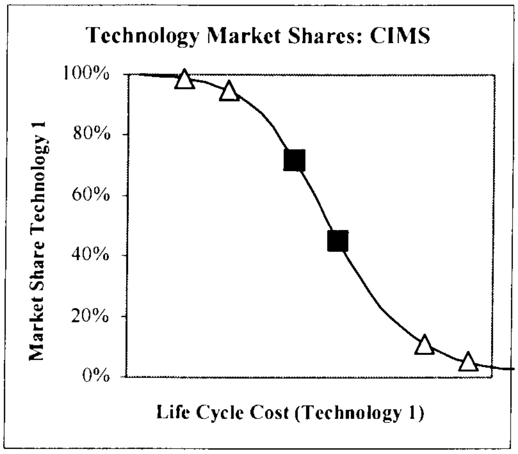

Figure 5.3 – CIMS market share curve

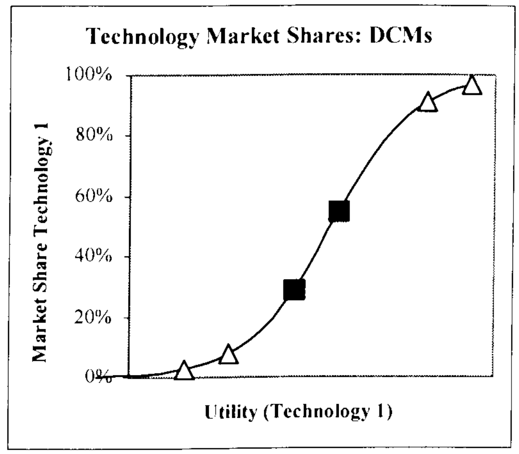

Figure 5.4 – DCM market share curve

The simplest CIMS parameter to obtain from a DCM is the discount rate, r, which Train (1985) has shown can be derived from a multi-nomial logit model using equation 5.2,

$$r = \frac{\beta_{CC}}{\beta_{OC}} \times (1 - (1 + r)^{-n}) \qquad \textit{(Equation 5.2)}$$

where β_{CC} and β_{OC} are the DCM coefficients for capital cost operating cost, and n is the lifespan of the technology. If n is sufficiently large, the term to the right of the multiplication sign approaches 1, and the discount rate can be calculated according to equation 5.3.

$$r = \frac{\beta_{CC}}{\beta_{OC}} \qquad \textit{(Equation 5.3)}$$

Table 5.5 summarizes some points when this simplification can be accurately used[26], where the validity depends on the discount rate. Because the technology lifespan for vehicles in CIMS is 16 years, and many studies have observed discount rates under 35% for vehicle purchases (Train, 1985), the simplification probably isn't valid in this case so the full equation will be used.

[26] The simplification was deemed to be accurate if it produced estimates for the discount rate within 1% of the full formula.

Discount Rate	Lifespan
5%	95
10%	49
15%	33
20%	26
25%	21
30%	18
35%	16
40%	14
45%	13
50%	12
55%	11
60%	10

Table 5.5 – Tech. life and discount rate combinations when equation 5.3 can be used

The intangible cost parameter i_j is calculated in a similar manner to the way capital costs are annualized, starting by determining the tradeoff between each non-monetary attribute and the operating cost (i.e. a capital recovery factor for each component of the intangible cost), illustrated by equation 5.4

$$CRF_k = \frac{\beta_k}{\beta_{OC}} \qquad \text{(Equation 5.4)}$$

where, CRF_k and β_k are the capital recovery factor and weighting parameter for each non-monetary variable k. The intangible cost parameter in equation 5.1, i_j, is then calculated by applying the capital recovery factory to each non-monetary variable, and summing all the terms according to equation 5.5

$$i_j = \sum^{K}(CRF_k \times X_k) \qquad \text{(Equation 5.5)}$$

where X_k is the value for non-monetary variable k, and K is the number of non-monetary variables, including the alternative specific constant[27]. The reason that the capital recovery factor is applied to each X_k is that no frequencies were given for any of the intangible costs in the survey, so respondents are assumed to have treated them as up front considerations similar to capital costs.

Equation 5.5 requires values for each X_k to be selected (the value for average SOV driving time for example) before i_j can be calculated. This requirement means that any of the intangible variables are fixed at a single X_k value for a given CIMS run, and cannot be dynamically altered during a simulation. They can however be changed prior to a run to describe a particular scenario (see section 6 for further discussion). As a possible future improvement to CIMS, it would be useful to be able to set X_k to different values in each time period. This approach would necessitate modifying CIMS to allow each i_j parameter to be defined independently for each period. For example, this improvement would allow changes in traveling time, or changes in fuel availability to be explicitly modeled by calculating the desired i_j parameters based on the discrete choice models and inputting them exogenously for each CIMS period.

Once the r and i_j parameters have been estimated, v can be selected so that the market shares predicted by CIMS match the market shares predicted by the discrete choice models. Based on equation 2.6 and 5.1, this relationship is shown by equation 5.6.

$$\frac{e^{V_j}}{\sum_{k=1}^{K} e^{V_k}} = \frac{\left[CC_j \times \frac{r}{1-(1+r)^{-n}} + MC_j + EC_j + i_j\right]^{-v}}{\sum_{k=1}^{K}\left[CC_k \times \frac{r}{1-(1+r)^{-n}} + MC_k + EC_k + i_k\right]^{-v}} \qquad \textit{(Equation 5.6)}$$

The difficulty with this relationship is that no direct analytical solution exists for v that will satisfy all combinations of attribute values that can occur within or across different simulations. Because the v parameter represents market heterogeneity, it shouldn't be affected by changes in attribute values. As a result, v should be selected to best satisfy the range of possible attribute values that are likely to occur during a simulation. To meet this requirement, an array of possible attribute value combinations was created for each set of technologies, and starting with a guessed value for v, each technology's market share was calculated using both sides of equation 5.6. The squared error between CIMS' market share and the DCM's market share were then summed across technologies

[27] The X_k's for the alternative specific constants equal one.

and attribute value combinations to yield a cumulative error term for the given v. Microsoft Excel solver was then used to find the v that resulted in the minimum cumulative error term, which was taken as the optimal estimate for v given the ranges of attribute values explored. Although this is essentially a calibration step (which was one of the problems with the current methodology for obtaining CIMS parameters), it is calibrating CIMS to a wide range of empirically estimated tradeoffs, and it is only calibrating a single parameter.

Calculating CRF_k for each alternative specific constant leads to an issue with market share allocation because the magnitudes of the alternative specific constants in a discrete choice model are arbitrary. As mentioned, DCM market shares are dictated by the differences in utilities, so only the differences between alternative specific constants matter. This means that the arbitrary anchoring of the alternative specific constants to zero doesn't effect the market share predictions. The alternative specific constants' anchor point does impact the calculation of CRF_k however, because CRF_k is directly related to each alternative specific constant's value. Even though a different value for CRF_k would lead to a different intangible cost parameter, i_j, the CIMS and DCM predictions would still be almost identical because v is determined after i_j, and would change to reflect changes in i_j[28]. Problems occur however when the results of one competition feed into another, as is the case in the mode choice competition. If the vehicle choice model's alternative specific constants were anchored at 10,000 instead of zero, the life cycle costs being propagated to the mode choice competition would be substantially higher, and the market shares for the non-vehicle modes would be much larger as a result. This problem is not a concern for this research because only the operating and fuel costs (instead of the life cycle costs) were transferred to the mode choice competition. To ensure that the problem is not encountered in the future, it is strongly recommended that discrete choice models be developed for any nodes that feed into one another, and that only explicitly declared attributes (capital, fuel, and operating

[28] This means that different anchor points in the discrete choice model could lead to any value for v, even though model performance would be unchanged.

costs) be passed between these nodes. Intangible costs would therefore need to be declared at each node separately based on that node's discrete choice model, and scaling problems would be avoided. If additional attributes are made explicit within CIMS in the future (travel time for example), these could also be propagated from node to node with the financial costs.

Even if the recommendations in the preceding paragraph are followed, the same issue leads to potential problems when calculating the welfare costs of a policy. Currently in CIMS, welfare costs are only calculated for tax-based policies by interpreting the area under a cost curve as society's willingness to pay (MKJA, 2002). This method would still work correctly, but more direct approaches at calculating welfare costs such as those discussed in Rivers and Horne (2003) would be more problematic. In these approaches, welfare costs would be calculated directly based on the stocks, and financial and non-financial costs for each technology in CIMS. Unfortunately, the component of the non-financial cost that stems from the alternative specific constants is essentially arbitrary, and the selection of an anchor point would have significant bearing on the final cost calculations. A potential solution for dealing with this problem would be to exclude the alternative specific constants' contributions to the intangible cost when calculating costs. As long as the discrete choice models are well designed, the alternative specific constants should constitute a relatively small portion of observed utility, so excluding them should not significantly impact cost predictions.

5.4 Resulting Parameters

The resulting v, and r parameters for the vehicle and mode choice models are shown in tables 5.6 and 5.7. The most likely estimate for the vehicle choice discount rate was calculated to be 22.6%, with 95% of the possible estimates falling between 10% and 59%. These estimates fall well within the wide range of values observed in similar studies, with Train's (1985) survey of the literature finding rates of 0% to 40% in vehicle choice decisions examined in eight studies. More recently, Ewing's (2000) results show discount rates of 19% or 70% depending on the coefficient examined, while Bunch's (1993) parameters leads to a rate of 0%[29] (none of these values were discussed in either of the papers). Although this range of estimates in the literature is quite wide, the fact that the rate observed in this study is well within the extremes lends confidence to the model results. The v estimates were selected as the best-fit values across 3,072 and 576 combinations of vehicle and mode choice attribute values. Depending on the subset of combinations, the solution varied from 2.79 to 2.99 for the vehicle choice models, and 1.99 to 2.26 for the mode choice models, showing that optimal solution is fairly robust to changing attribute values. These values for the v parameters are quite low compared to the current values used in CIMS (10 for vehicle choice and 6 for mode choice), which means that the new parameters will predict more market heterogeneity given similar life cycle costs. In other words, the less preferred technologies will receive more market share than they currently do. These changes have been made to a version of CIMS used solely for this project, but they are also recommended as modifications for future CIMS modeling projects.

Parameter	***Estimate***
v	2.9
r	22.6%

Table 5.6 – v and r for vehicle choice

Parameter	***Estimate***
v	2.2[30]
r	Not Applicable

Table 5.7 – v and r for mode choice

Although the i parameters for each technology in CIMS are functions of non-cost attributes, tables 5.8 and 5.9 present the most likely estimates for the vehicle and mode types based on the attribute levels provided by respondents in the telephone and mail surveys. The vehicle type estimates also include the possible modifiers for emissions and availability, which are not dependant on the attribute values[31]. The magnitudes of the

[29] Calculated assuming average driving distance of 17,000 km/year (Transport Canada, 2000).

[30] The lower v for the mode choice does not contradict the earlier conclusion that the mode shares were more influenced by attribute values than vehicle shares (see section 4.3). The lower v value is simply an artifact of the larger intangible costs in the mode choice model.

[31] The base values and modifiers for the vehicle types' i parameters presented in table 5.8 were not the exact values entered in CIMS because of a bug in the simulation software. CIMS does not allow negative operating costs, so to ensure that the sum of the i parameter and the existing O&M value were positive, a portion of the modifier was discounted and applied to the capital cost instead. The declining capital cost functions were adjusted so that their performance mimicked the original CIMS setup.

intangible cost parameters for vehicle types seem reasonable even though the availability modifiers are quite large, with a spread of over \$20,000 / year between the hybrid-electric and high-efficiency gasoline vehicles. These modifiers are large enough that they will completely dominate the vehicle type decision, but that is not unreasonable considering they are designed to simulate a case where only gasoline vehicles are available to the majority of the population. Until alternative vehicle technologies are made available to the public, they will not see significant adoption, regardless of how attractive their attributes are. The intangible costs for the mode choice are also quite large, but once again this makes sense based on the survey data, where respondents indicated that they felt time was the most important factor in their mode choice decisions.

Vehicle Type	**i – Base**	**i – Emissions Modifier**	**i – Availability Modifier**
Methanol	\$ 4,771 / year	\$ -469 / year	\$ 3,756 / year
Ethanol	\$ 4,013 / year	\$ -104 / year	\$ -2,452 / year
Electric	\$ -1,051 / year	\$ 0 / year	\$ 6,964 / year
Hybrid-electric	\$ -1,521 / year	\$ -235 / year	\$ 13,980 / year
Hydrogen Fuel Cell	\$ 270 / year	\$ 0 / year	\$ 0 / year
Propane	\$ 4,771 / year	\$ -496 / year	\$ 1,252 / year
Diesel	\$ 3,335 / year	\$ -417 / year	\$ -5,060 / year
Natural Gas	\$ 4,771 / year	\$ -417 / year	\$ -3,417 / year
Gas – High Efficiency	\$ 3,774 / year	\$ -287 / year	\$ -8,086 / year
Gas – Low Efficiency	\$ -633 / year	\$ -835 / year	\$ -5,895 / year

Table 5.8 – Estimates of i for each vehicle type

Mode	**i**
SOV	\$ 6,352 / year
HOV	\$ 7,828 / year
Transit	\$12,394 / year
Walk/Cycle	\$11,947 / year

Table 5.9 – Estimates of i for each mode type

As a validation step for the techniques mentioned in this section, the market shares predicted by the DCM's are compared with the market shares predicted by CIMS using the DCM derived parameters. Figure 5.5 through 5.8 and 5.9 through 5.12 show these comparisons for four validation scenarios of mode and vehicle choice, with the details of each scenario available in appendices 4 and 5. The predicted market shares resulting from the discrete choice models and CIMS based on the discrete choice models are extremely close. The discrepancies in the vehicle choice comparisons are slightly larger than their mode choice counterparts because the greater number of choices makes the fit for the v parameter less exact. In a two-technology case, the fit between CIMS and the DCM would be almost perfect. The steps described in the previous section have been programmed in Excel 2000 so that CIMS parameters can be easily estimated for any desired scenario of attribute values. A variety of these scenarios and the resulting i parameters are presented in appendix 9, with their use in CIMS discussed in section 6.

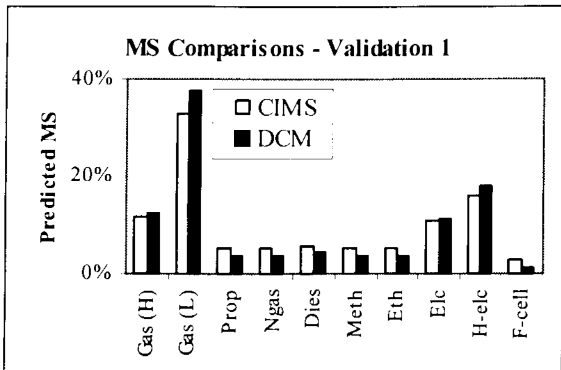

Figure 5.5 – Vehicle choice validations - Scenario 1

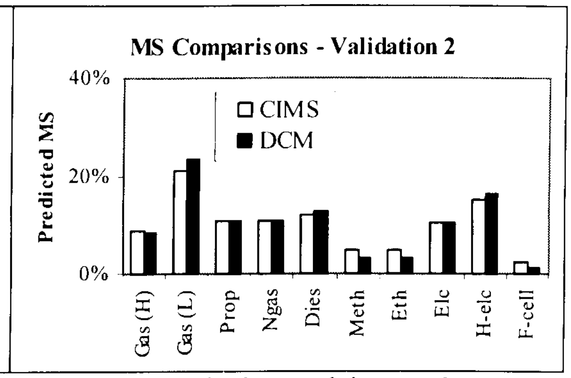

Figure 5.6 – Vehicle choice validations - Scenario 2

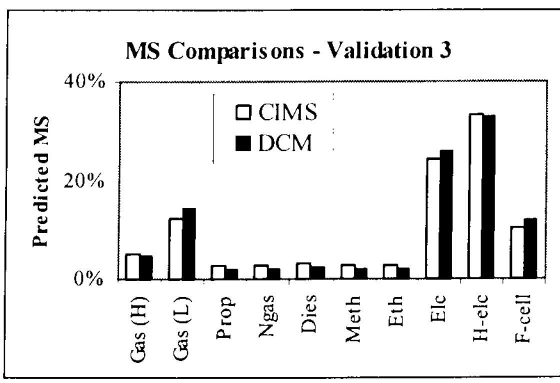

Figure 5.7 – Vehicle choice validations - Scenario 3

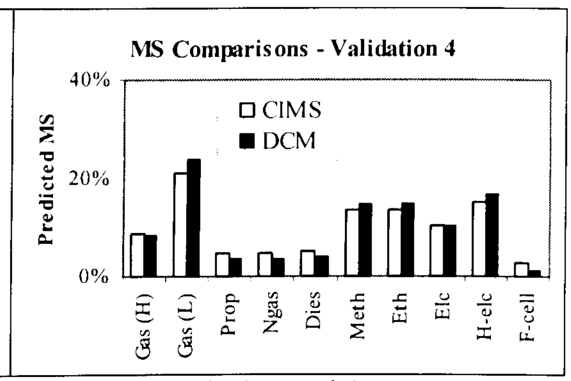

Figure 5.8 – Vehicle choice validations - Scenario 4

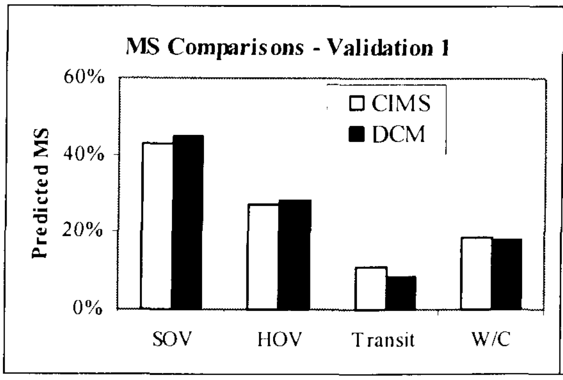

Figure 5.9 – Mode choice validations - Scenario 1

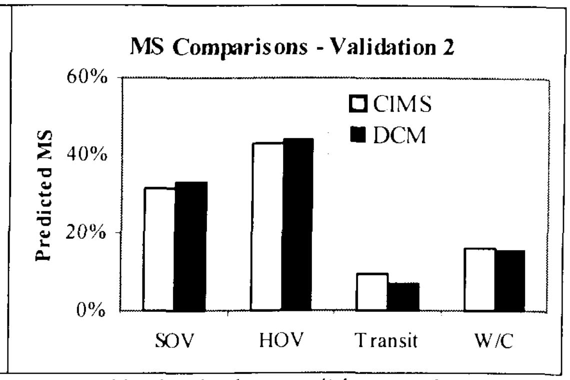

Figure 5.10 – Mode choice validations - Scenario 2

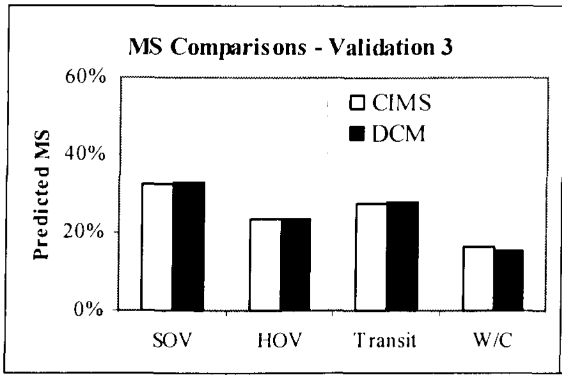

Figure 5.11 – Mode choice validations - Scenario 3

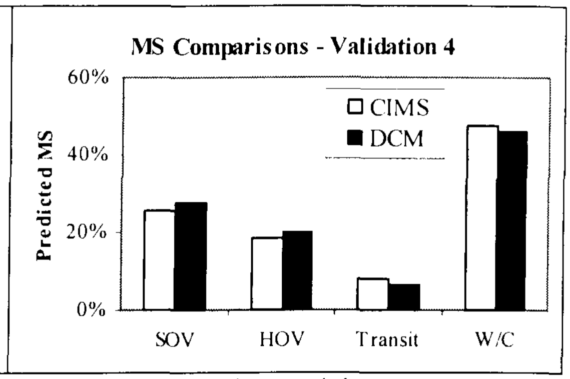

Figure 5.12 – Mode choice validations - Scenario 4

5.5 Propagating Uncertainty Into CIMS

The steps outlined in the preceding section only discuss how to estimate single values for behavioral parameters while it has already been noted that the β parameters they are based on are only the best estimates. Each of these alternative values could lead to different model predictions for stocks, emissions, and costs, and as such, it would be advantageous to be able to propagate the information gained about preference uncertainty into an energy-economy model. Doing so would allow the advantages of including uncertainty raised by Morgan and Henrion (1990), namely identifying key factors, facilitating comparison, and enabling future elaboration, to be exploited. In addition, a full examination of uncertainty also opens the possibility of determining the expected outcomes of a policy scenario, which are defined as the sum of the possible outcomes individually weighted by their probability of occurrence. Rechow (1994) explains that the expected outcome can differ from the most likely outcome if either the magnitude of possible outcomes or their probabilities of occurrence are asymmetrically distributed. Whenever this is the case, making decisions based on the most likely outcome (i.e. not accounting for uncertainty) can lead to sub-optimal actions. As an example, take a situation where policy A would lead to low emissions in the most likely scenario, but disproportionately high emissions if a certain set of parameter estimates turns out to be true. If policy B predicts slightly higher emissions levels for the most likely parameter estimates, but isn't accompanied by the extremely negative outcomes for other estimates, it could be the decision maker's preferred action. Before being able to take advantage of these strengths, the challenge that remains is finding a way to propagate the information gained in section 4.4 into CIMS in an accurate and efficient manner.

Currently, energy-economy models generally recognize the importance of uncertainty, but their actual treatment is inadequate, commonly neglecting the issue entirely, or simply exploring a selection of possible scenarios (Schimmelpfennig, 1996). Some of the stronger approaches include Manne and Richels (1994), and Fiddaman (2002) who have addressed uncertainty using top-down models (Global 2100 and FREE respectively). Manne and Richels surveyed experts to develop distributions for GDP growth, elasticities of substitution, AEEI, availability of economically competitive renewable substitutes to coal-fired electricity, and the costs of non-electric liquid fuel backstops. Fiddaman developed subjective distributions for a similar set of parameters. Their works account for a wide range of uncertainty, and they produce predictions for global carbon emissions ranging between 5 and 25, and 5 and 20 gigatons in 2030 respectively. Although useful, neither of these models are based on empirical data, nor do they explicitly account for the uncertainty in preferences for different technologies. This avoidance of preferences could be attributed to the conventional neoclassical economic assumption that preferences are static in the short-run, and unchanged by government or market influences. This would be unfair, as accounting for uncertainty is not necessarily a rejection of these assumptions, and should more correctly be interpreted as a recognition that consumer preferences cannot be perfectly observed and modeled by an outside observer. Therefore, even if preferences are static, preference modeling should allow for a range of possible preferences. Techniques that account for behavioral uncertainty using empirically estimated confidence intervals have been demonstrated by Stavins (1999) in the specific context of converting farmland to forests to sequester carbon, and also discussed by Jaccard et al. (2003). These approaches are beneficial in that they show a range within which the most likely outcome is likely to occur, but they do not provide information on the distribution of outcomes, which is critical when determining the expected costs of a policy.

A logical approach to comprehensively account for behavioral uncertainty in CIMS would be to solve v, i, and r for each combination of β parameters, and use values from the joint probability function for the β parameters to develop a joint probability distribution of v, i, and r. This distribution could then be sampled from, and with each set of v, i, and r parameters used to run CIMS, the resulting simulation outputs could be compiled to develop probability distributions for technology stocks, costs, and emissions. Unfortunately the time required for this approach is not feasible for two reasons. First, solving v, i, and r already takes considerable time, so repeating these steps for each combination would be too time consuming, especially considering that it would need to be done for each change in attribute values that would lead to different i values. Second, CIMS already takes upwards of ten minutes to run using single parameter estimates, and that time would become unmanageable if parameter estimates needed to be sampled hundreds of times for a single CIMS run.

In order to circumvent the problems discussed above, an alternate approach involves calculating market shares normally in CIMS (using the most likely estimates of v, i, and r), and then randomly modifying those market shares based on the market share distributions obtained in section 4.4. To describe the process more specifically, imagine a CIMS technology competition between three technologies. First, assuming that the market shares are approximately normally distributed (limited within the range of 0% to 100%), a standard deviation is selected for each technology as a function of that technology's most likely market share by fitting the proposed distribution to the market share curves developed for vehicle and mode choice in figures 4.44 through 4.51. After the initial market shares are calculated, the following four[32] steps are repeated until smooth distributions are obtained for the three hypothetical technologies. First, a revised market share is sampled for the first technology using its initial market share as the distribution's mean. Second, the shares of the remaining two technologies are scaled so that their relative shares equal the initial proportions, and the total market share sums to 100%. Third, a market share is sampled for the second technology using its revised market share as the distribution's mean. Finally, the third technology's market share is assigned so that the sum of the three shares equals 100%. This approach is only mathematically valid if the market share distributions are independent of each other, meaning that sampling a certain market share for the gasoline vehicles doesn't affect the likelihood functions of the remaining vehicle types. This assumption was not rigorously tested, but the symmetry of the marginal distributions for each β parameter, and the symmetry of the market share distributions shows that any dependencies are probably negligible.

Standard deviations for the distributions of market shares for vehicle types and mode types were described according to the quadratic equations shown in equations 5.7 and 5.8 respectively[33], where MS refers to the maximum likelihood estimate for market share.

$$sd_{VC} = -0.0004963 \times \mathrm{MS}^2 + 0.04963 \times \mathrm{MS} + 0.5186 \qquad \textit{(Equation 5.7)}$$

$$sd_{MC} = -0.0004284 \times \mathrm{MS}^2 + 0.04284 \times \mathrm{MS} + 0.5055 \qquad \textit{(Equation 5.8)}$$

These equations produce standard deviations between 0.52% and 1.76% for vehicle type choice, and 0.51% and 1.57% for mode choice, which come very close to approximating the original distributions. The steps to produce distributions of vehicle type and mode market shares were programmed using an Excel 2000 macro, which also calculated the related distributions for stocks and emissions. The macro utilized CIMS outputs, and the process was iterated 10,000 times to achieve smooth distributions that were unbiased

[32] For competitions with more or less than three technologies, the number of steps to be repeated is equal to one less the number of technologies multiplied by two.

[33] Quadratic equations were used because they allow the function to mimic the behavior of decreasing uncertainty as the most likely market shares approach 0% or 100%. A simple direct relationship with market share would not have facilitated this performance.

from the maximum likelihood estimates. The results of this analysis are presented in the following section, which examines a number of different policy scenarios.

This approach is subject to three limitations that should be discussed before proceeding. First, and probably most importantly, the uncertainty being discussed in this paper only refers to the uncertainty surrounding consumer preferences. In addition to this source of uncertainty, there is also a considerable degree of uncertainty in the technical data within CIMS, and its magnitude relative to the behavioral components is unknown. To properly address this issue, a detailed review of the costs and emissions data in CIMS is required[34]. Second, the techniques have only been applied to the personal urban transportation technologies in CIMS, and until the majority of the key technologies are approached in a similar manner, estimates of uncertainty for the economy would be considerably understated. This problem is easily solved because the aforementioned techniques could be extended to other sectors of the model once the underlying parameters have uncertainty distributions associated with them. Third, the uncertainty in each time period is assessed independently, meaning that an unlikely event in period one can't influence the likelihood of outcomes in subsequent periods. This limitation results in an underestimation of uncertainty, which could only be resolved if parameter values were sampled as CIMS was running.

Despite these limitations, the techniques described in this section provide a workable solution to the problem of incorporating empirically estimated behavioral uncertainty in an energy-economy model like CIMS, and as such represent a valuable advancement in the presentation of results. An inseparable challenge from quantifying uncertainty is successfully conveying the ideas so that they can be understood and incorporated into a policy analysis. Using probability distributions to quantify uncertainty (as opposed to more traditional frequentist approaches such as confidence intervals) increases the challenge of conveying information because many people are not familiar with the

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[34] Much of CIMS' technology data was reviewed between 1999 and 2001 by experts as part of the model's application to estimating GHG emission reduction costs for the National Climate Change Implementation Process in Canada, but little was done to address the uncertainty in this data.

technique. Instead, it is natural to prefer to focus on single outcomes, while marginalizing many other, slightly less probable outcomes (Morgan and Henrion, 1990). Teaching people to recognize the non-zero probability associated with a wide range of outcomes is probably not the simplest way of conveying uncertainty, but because of the benefits discussed earlier, the endeavor is worthwhile. This is not to say that traditional statistical techniques are no longer useful[35], but instead that a probabilistic approach offers additional benefits, which should make it the preferred tool when feasible.

[35] For example, confidence intervals are a much more visually accessible tool for showing cost or emission time trends, because using probability distributions for outcomes necessitates a three-dimensional representation of the data.

6 Policy Simulations

This section demonstrates CIMS' new capabilities to model a range of policies effecting various decision attributes in both mode and vehicle choice. More specifically, sections 6.1 through 6.4 look at the business as usual case, a carbon tax, incentives for non-gasoline vehicles, and incentives for non-single occupancy vehicle modes. The first two simulations do not demonstrate new CIMS capabilities, but they do include the revised baseline parameters, so for the resulting predictions will likely be different from existing CIMS forecasts. The last two policies are designed specifically to demonstrate the new attributes incorporated into the CIMS parameters for mode and vehicle choice, and they could not have been reliably simulated prior to this research. All of the analysis for this section uses the results of runs for Ontario's transportation sector because it accounts for 31% of national transportation emissions (Transport Canada, 2000). With the exception of base stocks and demands, the transportation models do not vary from region to region, so these results could easily be scaled up to reflect national predictions, or the modifiers could be applied to each region to facilitate national runs.

In each of the simulations, the output information focuses on the transportation sector's CO_2 equivalent emissions in five-year time increments from 2005 to 2035. In the interests of simplicity, market shares are only presented for the unmodified business as usual case (full market shares are available in appendix 10). Costs are not presented in this analysis because the two new policies being tested have associated financial costs (financing additional fuel availability, and building bike lanes for example) that have not been quantified. Without a better estimate for these policy costs, reporting financial or social costs would be highly misleading. This information would ideally be available before deciding between policies, but it is not required for the demonstrative purposes of this section. As discussed, the discrete choice models forming the foundation of the new CIMS parameters are not perfect, and two steps are taken to account for this uncertainty in the simulations. First, the availability and emissions modifiers developed for the vehicle choice alternative specific constants in section 5.4 were included by running four variations of each simulation. The different runs are shown in table 6.1. Second, emissions distributions were calculated for the year 2035[36] to show the range of outcomes that the data implies to be plausible. Additionally, policies could have been simulated with and without minimum mode shares to account for mode availability (introduced in section 4.2). This step has been omitted from this research because it was considered less important than looking at the different policies and the uncertainty surrounding the vehicle choice model, which already resulted in 16 different cases to analyze.

	Run 1	**Run 2**	**Run 3**	**Run 4**
Include the availability modifiers	No	Yes	No	Yes
Include the emissions effect modifiers	No	No	Yes	Yes

Table 6.1 – Modifiers to include in different runs for each policy

The following results for mode shares are referring to usage, and not ownership. This issue has been highlighted by MKJA (2002) who point out that although a person may choose to take transit to work, they may continue to own that vehicle for other purposes. CIMS produces aggregate mode splits, meaning that it doesn't indicate what percentage of the population is using each mode, instead showing the percentage of total travel demand that is satisfied by each mode. For example, CIMS does not differentiate between half the population riding their bikes all the time or the entire population riding their bikes half the time. This issue is not critical to emissions, because they are dictated entirely by usage patterns, but it is much more important for costing, because the actual vehicle stocks (instead of their usage) dictate how much capital investment is made. MKJA (2002) handle this issue by calculating costs under the primary assumption that all changes in mode choice lead to changes in vehicle ownership, and second that no changes in mode choice lead to changes in vehicle ownership. This treatment of costs leads to national financial differences of $1,000,000,000 to $18,000,000,000 (in 1995 dollars) in the transportation sector for taxes of $10 to $150 per tonne of carbon. This sensitivity analysis could be refined based on figure 6.1, which presents some survey

[36] Only one period's results are displayed here because the uncertainty is handled independently for each period, so the figures for different periods will all possess similar characteristics around the most likely estimates.

results showing how many people think their families could make due with fewer vehicles if their traveling habits changed. In total, only 24% of respondent's said they could meet their traveling needs with fewer vehicles, so calculating costs assuming that either 0% or 50% (instead of 0% or 100%) of the population give up their vehicles would provide a more concise range for the sensitivity analysis.

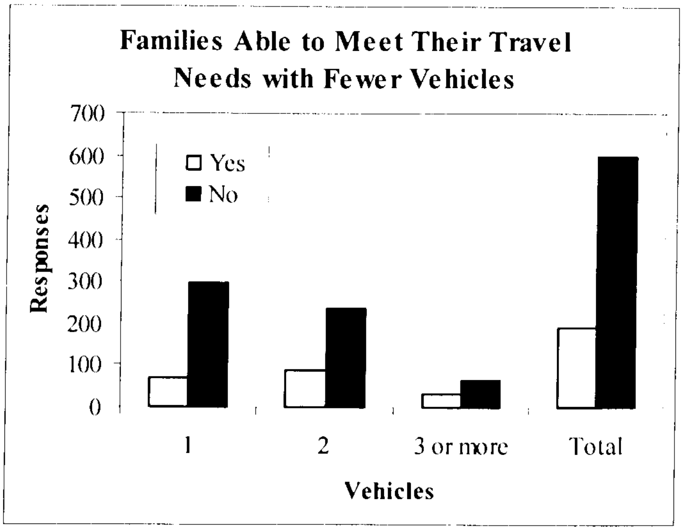

Figure 6.1 – Respondents' ability to use fewer vehicles

6.1 Business As Usual

Figures 6.2 and 6.3 show the vehicle type and mode shares for the unmodified (run 1) business as usual case. The new vehicle emissions by period from each of the business as usual runs are displayed in figure 6.4, while figure 6.5 focuses on the range of possible emissions in 2030. In all runs, new vehicle emissions increase quickly until 2010 because the older vehicles are quickly being replaced. After this initial rise, the rate slows to a more gradual increase reflecting an ongoing growth in transportation demand. Also relatively common across runs are the mode share patterns, with single occupancy vehicles gaining the most market share (35%), followed by carpools (30%), walking and cycling (20%), and transit (10%). The stability in mode shares is in stark contrast to the vehicle type shares, which are dramatically influenced by the different modifiers, with the high and low efficiency gasoline vehicles moving from a combined 35% market share in run 1 to 98% in run 4 where they are as attractive as possible. It is interesting, but believable, that considerable swings in the vehicle market can have such little impact on the choice of modes. The stability occurs because only the operating and fuel costs of the vehicles are passed to the mode choice competition, and these assert much less influence on mode choice than the non-financial factors such as driving time.

Although minimal, the availability modifier (used in runs two and four) did have some influence on mode shares from period to period, as the single occupancy vehicles increased their market share at a slightly faster rate when availability wasn't accounted for. This difference is explained by the increasing shares of hybrid-electric and electric vehicles in runs one and three, both of which have lower fuel costs than the vehicles they are replacing. Runs two and four are different because the availability modifier makes these vehicle types too expensive relative to gasoline vehicles. This difference amplifies over time because once hybrid electric and electric vehicle begin capturing market share their capital costs decline to simulate economies of scale and learning[37]. As the capital costs decline, the vehicle types gain more market share, causing the weighted average fuel and operating costs for vehicles to drop even further. The effect of the modifiers is also illustrated through the emissions figures, where carbon dioxide output increases from runs one to three, to two, to four. The most likely rankings make sense because both modifiers make more polluting vehicle types more attractive, and as expected, the availability modifier (run 2) exerts a greater influence on market shares than the emissions modifier (run 3). It is interesting to note however, that the uncertainty distributions presented in figure 6.5 show that there is considerable overlap in these distributions, meaning that these rankings aren't necessarily fixed.

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[37] The declining capital cost feature of CIMS does not apply to mature technologies such as gasoline vehicles.

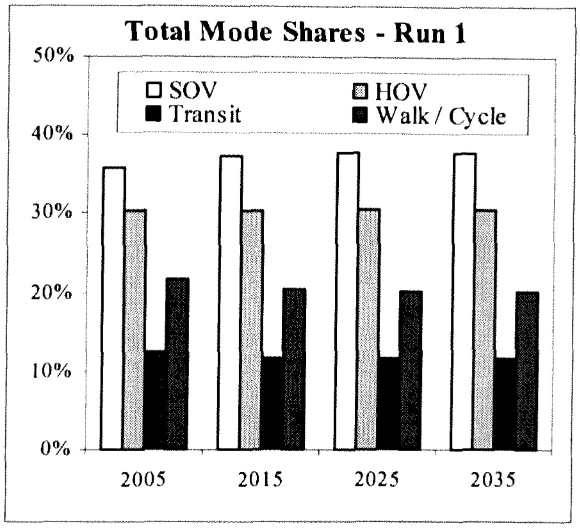

Figure 6.2 – Mode Shares – Run 1 (No Modifiers)

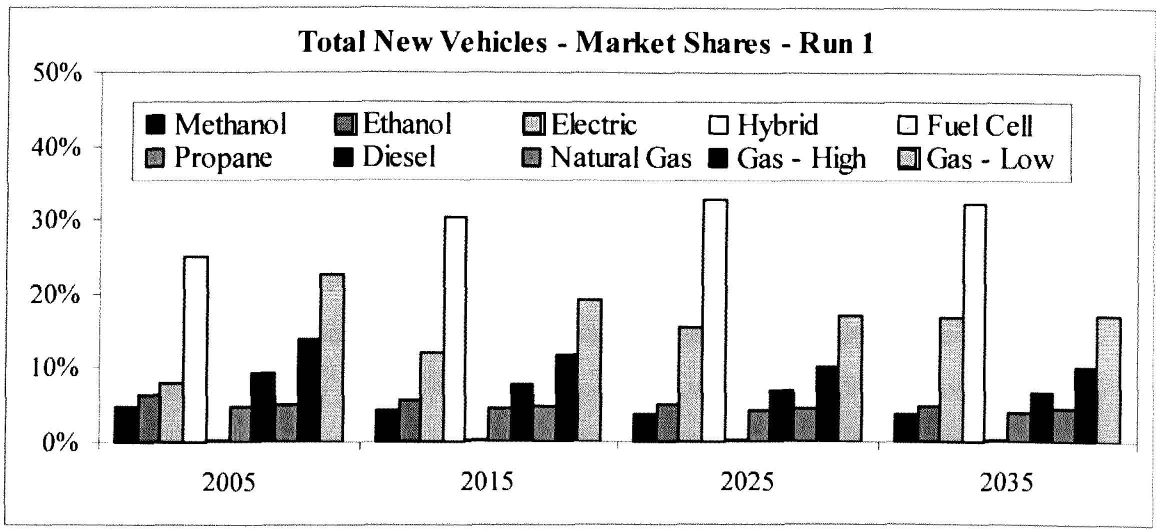

Figure 6.3 – Vehicle Type Shares – Run 1 (No Modifiers)

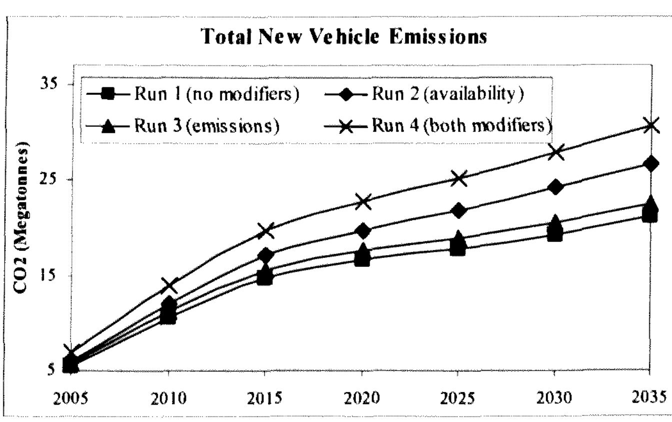

Figure 6.4– Total new vehicle emissions for the business as usual scenario

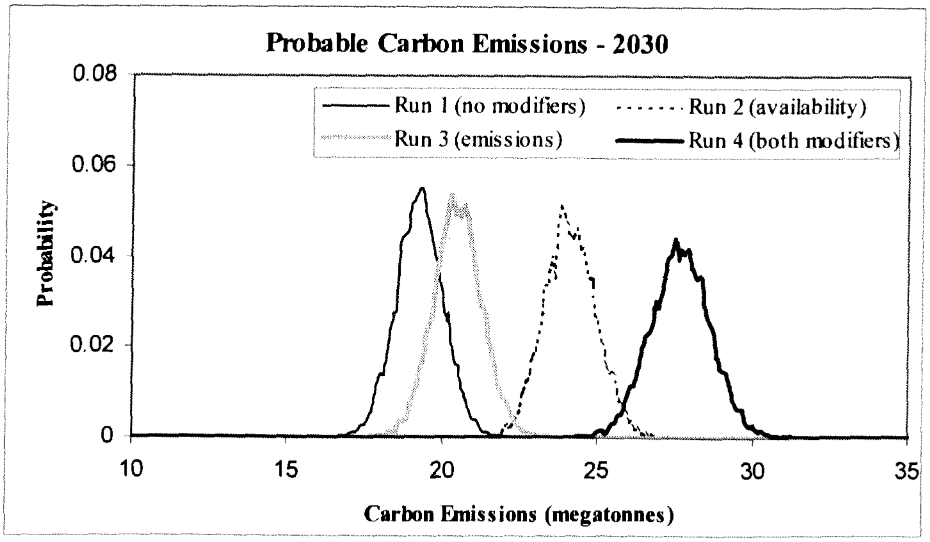

Figure 6.5 – Probability[38] of new vehicle emissions for the BAU scenarios in 2030

6.2 Carbon Tax

The new vehicle emissions for runs one through four with a $50/tonne carbon tax are shown in figures 6.6 through 6.9 in comparison with the equivalent business as usual run. Figure 6.10 also shows these emissions in 2030 with their associated probability distributions. The associated vehicle and mode shares are available in appendix 10. The tax results in a modest reduction in carbon dioxide emissions between one and five megatonnes per year. The reduction occurs because market share for the low efficiency gasoline vehicles, which are most effected by the tax, has been distributed relatively evenly between the other vehicle types. Emissions reductions are the greatest in run four because the gasoline vehicles have more market share in the business as usual case, so even though a comparable percentage of consumers are predicted to switch, the absolute number changing is greater. If the reported emissions included all modes, the reduction would be slightly larger because the zero emission option of walking and cycling gains market share at the expense of the other three modes.

[38] The probability associated with a given emissions level is inversely related to the number of possible emissions outcomes assumed to be possible. In other words, as finer intervals are explored the associated probabilities get smaller. In this figure emissions were evaluated in 0.1 megatonne intervals, so a 0.01 probability for 20 megatonnes mean that there is a 1 percent chance that the emissions will be between 19.5 and 20.5 megatonnes.

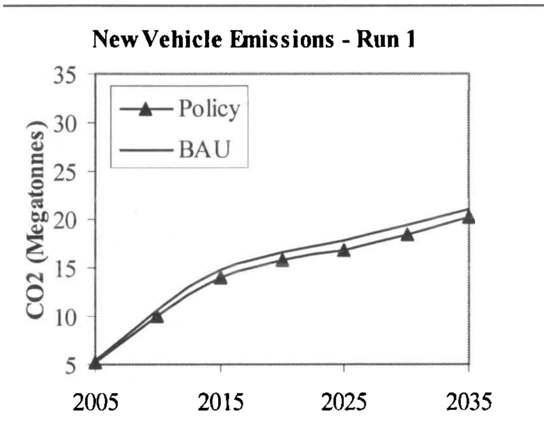

Figure 6.6 –New vehicle emissions (no modifiers)

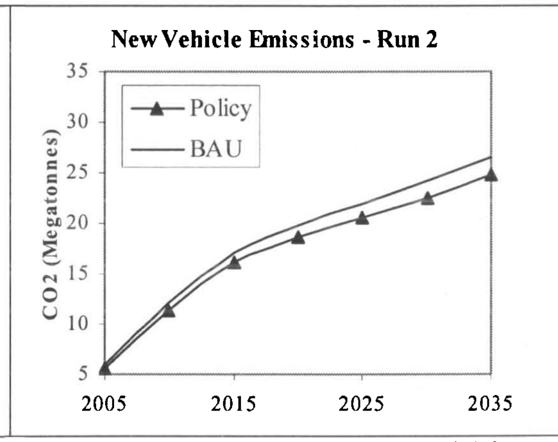

Figure 6.7 – New vehicle emissions (availability)

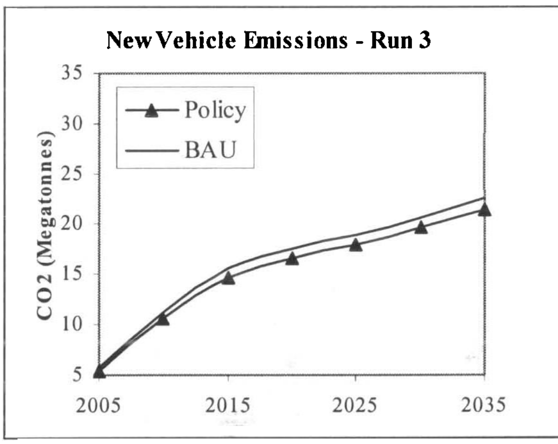

Figure 6.8 – New vehicle emissions (emissions)

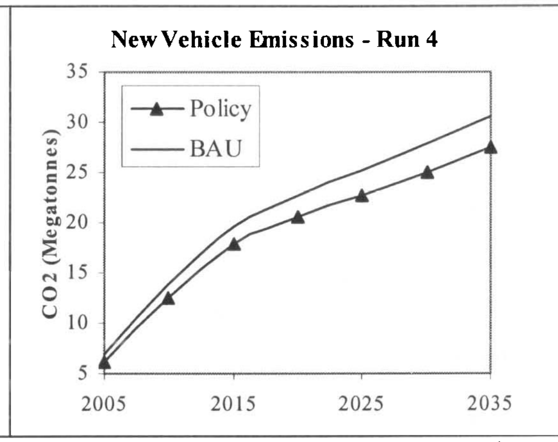

Figure 6.9 – New vehicle emissions (all modifiers)

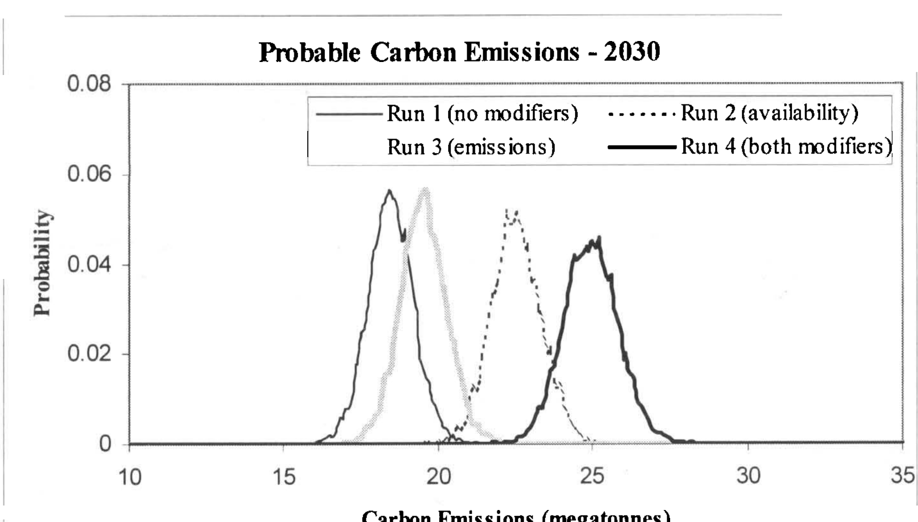

Figure 6.10 – Probable new vehicle emissions for carbon tax scenarios in 2030

6.3 Incentives for Non-Gasoline Vehicles

The non-gasoline incentives entailed increasing the fuel availability of methanol, ethanol, natural gas, propane, diesel, and hydrogen fuel cell vehicles by 25%, giving express lane access to hydrogen fuel cell and electric vehicles, and increasing the power of every vehicle except diesels and low-efficiency gas. Using the existing financial cost attributes, a surcharge of $1,000, and $3,000 was also applied to high, and low efficiency gasoline vehicles respectively. The annual emissions resulting from each run using these incentives/disincentives are shown in figures 6.11 through 6.14, while figure 6.15 shows the 2030 emissions including uncertainty. The market shares for mode and vehicle types for each run are available in appendix 10.

The emissions reductions resulting from the non-gasoline incentives were slightly greater than the $50/tonne tax, ranging from 1 to 6 megatonnes depending on the combination of modifiers. The incentives have the desired affect of discouraging people from choosing the high or low efficiency gasoline vehicles, most of which chose hybrid-electric and electric vehicles instead. The impact of these policies increases with time because they also cause the capital costs of hybrid-electrics and electrics to decline, making them even more attractive. Despite all of the incentives, the capital cost of hydrogen fuel cell vehicles still makes them prohibitively expensive, as they are unable to capture any market share. One of the most interesting effects of this policy is that it actually increases (albeit by less than 1%) the SOV and HOV market shares. The reason for this change is that the policy encourages people to use more environmentally benign vehicles, which happen to have cheaper fuel costs. Switching to these types of vehicles lowers the weighted average fuel cost for all vehicles, making the SOV and HOV options more attractive mode choices. This result illustrates the potential pitfalls of the rebound effect, which describes a situation where people have saved money on energy (fuel) consumption, and then put those savings into different kinds of consumption, thereby negating some of the energy savings (Jaccard and Bataille, 2000). The integrated nature of CIMS allows these types of counter-intuitive interactions to be foreseen and quantified, where they would have otherwise been missed in an isolated vehicle choice model.

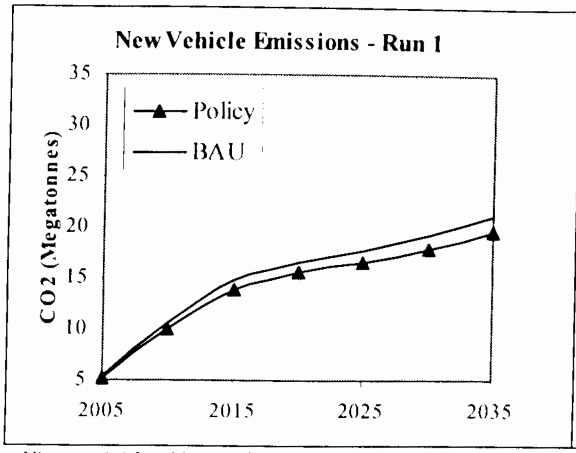

Figure 6.11 New vehicle emissions (no modifiers)

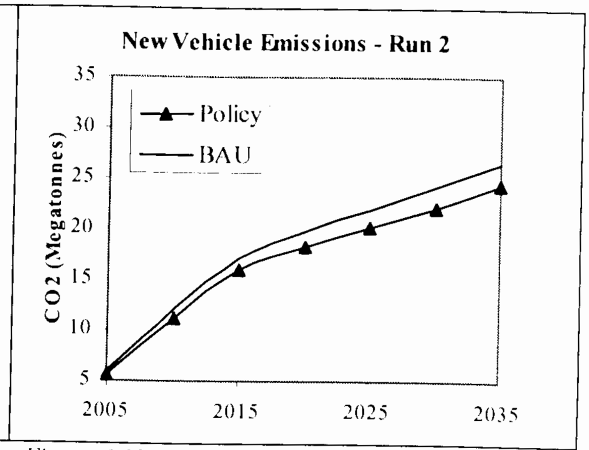

Figure 6.12 New vehicle emissions (availability)

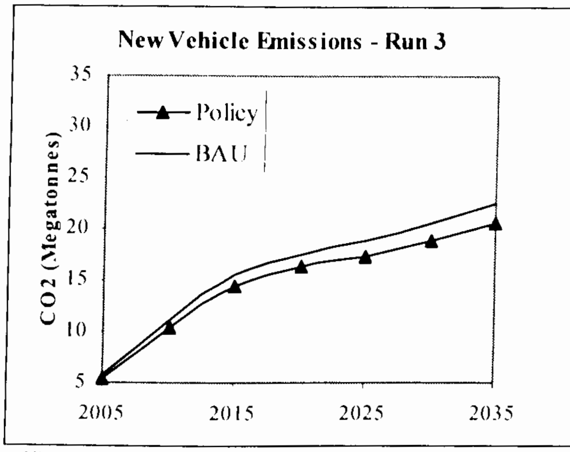

Figure 6.13 New vehicle emissions (emissions)

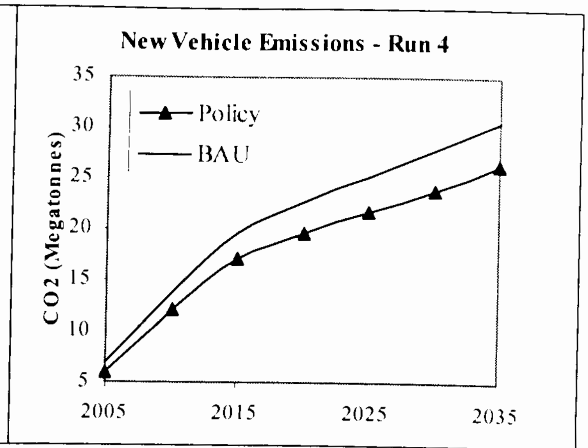

Figure 6.14 - New vehicle emissions (all modifiers)

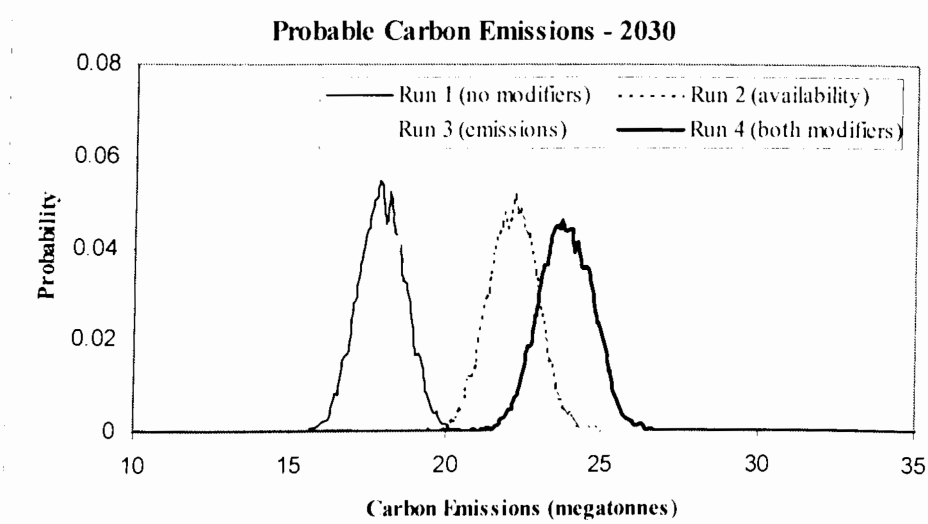

Figure 6.15 Probable new vehicle emissions for non-gas scenarios in 2030

6.4 Incentives for Non-Single Occupancy Vehicle Modes

The non-SOV incentives included increasing SOV driving time by 15%, decreasing the in-vehicle time of all other modes by 20%, reducing the waiting time for transit by two thirds, cutting the number of transfers in half, and increasing the percentage of commutes with bike route access by 50%. In additional to non-financial policy levers, the cost of transit was also reduced by $400 per year. The annual emissions resulting from these incentives / disincentives are illustrated in figures 6.16 through 6.19, while figure 6.20 illustrates the uncertainty surrounding year 2030 emissions. The market shares for mode and vehicle types are available in appendix 10.

The non-SOV incentives resulted in the greatest emissions reductions, ranging from five to ten megatonnes depending on the combination of modifiers, which are slightly exaggerated because they don't account for the marginal increase that will result from greater transit use. It should be noted, that these large reductions are not an indication that the mode switching policies are superior, because the costs of the different policies are not accounted for in this analysis. The findings are important however, because they show an additional potential for emissions reductions through mode switching that has not been revealed in earlier simulations with the CIMS model (MKJA, 1998 and MKJA, 2002). The emissions reductions are entirely caused by the almost 10% decline of market share for single occupancy vehicles. The market share for carpooling also decreased slightly, while walking and cycling, and transit have both experienced significant increases (5% and 10% respectively).

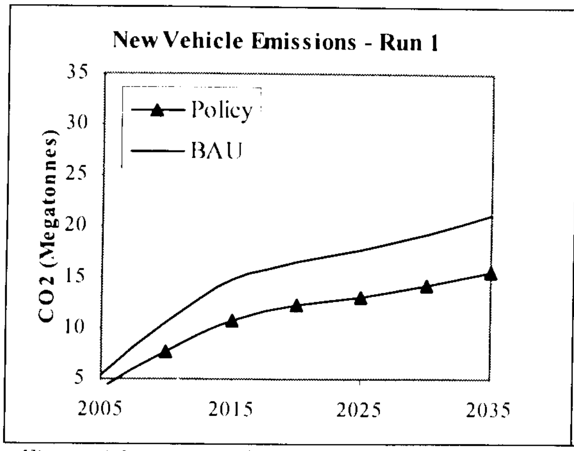

Figure 6.16 - New vehicle emissions (no modifiers)

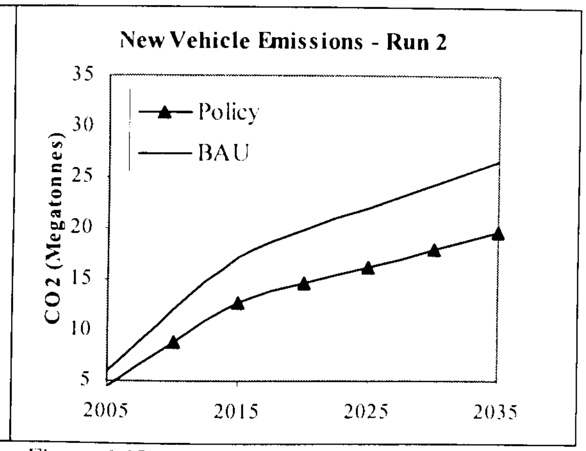

Figure 6.17 - New vehicle emissions (availability)

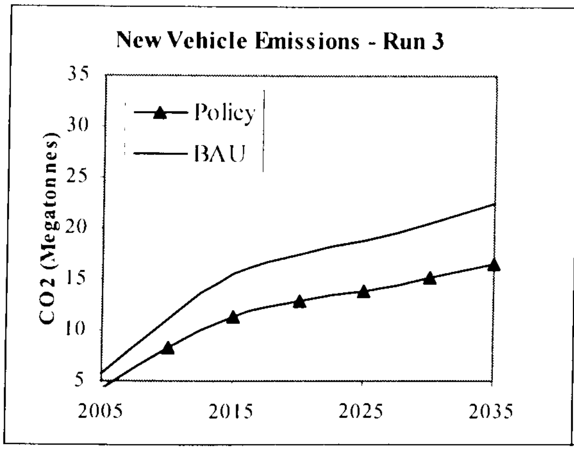

Figure 6.18 – New vehicle emissions (emissions)

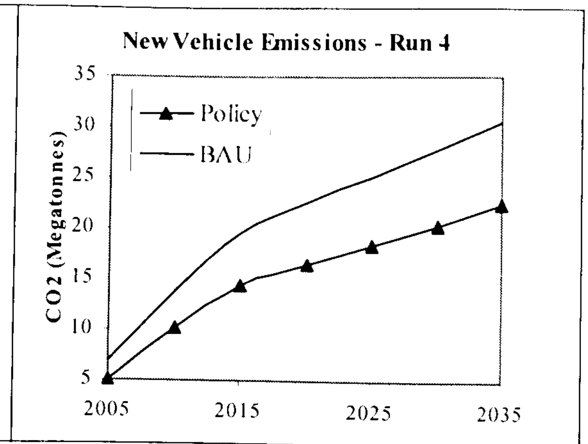

Figure 6.19 – New vehicle emissions (all modifiers)

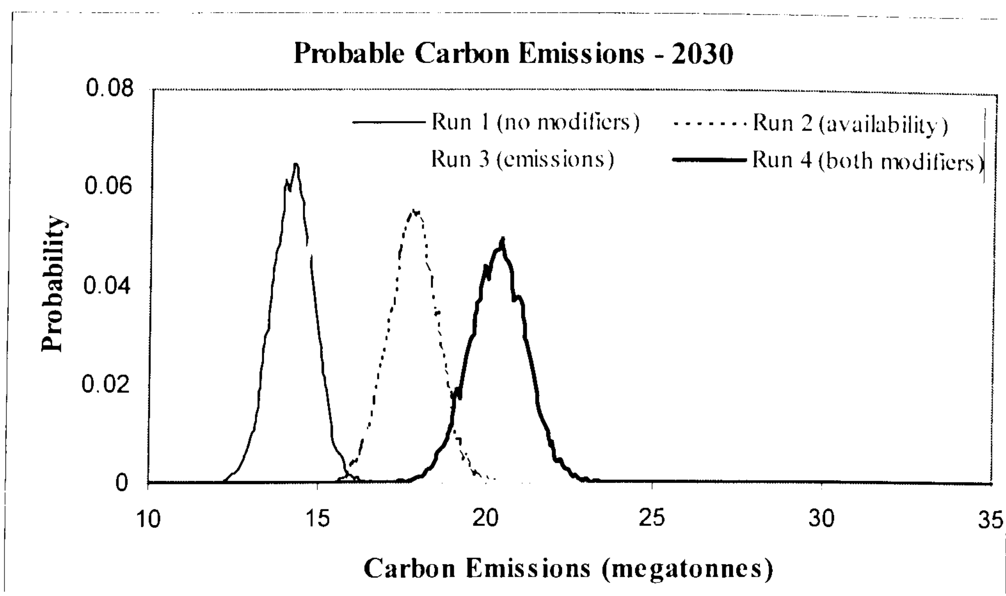

Figure 6.20 - Probable new vehicle emissions for non-SOV scenarios in 2030

7 Conclusions

The primary goal of this research was to develop a rigorous method to improve the behavioral parameters in CIMS. Doing so would help bridge the traditional gap between top-down and bottom-up approaches to energy-economy modeling by incorporating both technological detail, macro-economic feedbacks, and empirically estimated, behavioral realism into a single model. These improvements would advance beyond previous efforts to develop a hybrid model by providing more accurate model predictions and allowing a wider range of policies to be simulated. Both of these improvements would be of significant benefit to policy makers who can be limited and confused by the divergent modeling approaches currently used. To place this goal within a tangible context, personal urban transportation (mode choice and vehicle choice specifically) was selected as the research focus. This sector of the Canadian economy is significant in terms of environmental impact (accounting for approximately 13% of national carbon dioxide emissions), and the consumer decisions that define the sector are also an interesting mix of financial and non-financial factors. These combined characteristics make personal urban transportation an ideal candidate for hybrid modeling. As discussed in the following sections, these goals have largely been met, but new challenges have emerged and each stage of the project has offered lessons that will benefit anyone charting a similar research course in the future. Section 7.1 summarizes the underlying discrete choice models, which bring the behavioral realism to CIMS. Section 7.2 follows with a discussion of where the project has left hybrid modeling, and section 7.3 points to future research agendas for hybrid models.

7.1 Behavioral Realism in Personal Urban Transportation

After identifying the general research goals and context, discrete choice models were selected as an econometric modeling approach that could provide the detailed representation of consumer decision-making behavior needed in a hybrid model. An additional strength of discrete choice models is that they can be compatible with the existing parameter structure of CIMS and, although not perfect, the match between DCM and CIMS predictions can be very good. The data needed to estimate these models was obtained by surveying a random sample 1,154 Canadians living in urban centers about their preferences for different commuting modes and vehicle types. Although some biases were inevitably present, the combination of a high response rate (77%), a wealth of respondent comments, and general high quality responses led to the conclusion that the survey data was highly representative of the respondent population. Despite the success of the data collection phase of the research, the process was challenging, and a possible improvement would be to follow-up on a sampling of the initial responses. If respondents could have been interviewed to explain their choices in more detail, a number of lingering questions about the meaning of certain types of responses could have been resolved. Such follow-ups would need to be carefully considered because they would require additional time and money, and would probably need to be accomplished as multiple stages in a larger research project.

The otherwise successful survey produced a rich data set that permitted the estimation of highly significant multi-nomial logit models, in which all of the attribute coefficients had the expected signs. These results show that the attributes and alternatives used were meaningful to respondents, and that they were important factors in mode and vehicle choices. The final vehicle choice and mode choice utility formulations are shown again in equation 7.1 through 7.4 and 7.5 through 7.9 respectively. In addition to the maximum likelihood estimates, the techniques developed in this research have shown how to look at the probability associated with a range of parameter values.

Vehicle Choice Utility Formulation

$$V_{Gasoline} = -9.0 \cdot 10^{-5} \cdot CC - 4.6 \cdot 10^{-3} \cdot FC + 1.2 \cdot FA - 0.2 \cdot EXP - 0.2 \cdot POW - 1.7 \qquad \textit{(Equation 7.1)}$$

$$V_{Alt\ Fuel} = -9.0 \cdot 10^{-5} \cdot CC - 4.6 \cdot 10^{-3} \cdot FC + 1.2 \cdot FA - 0.2 \cdot EXP - 0.2 \cdot POW - 2.0 \qquad \textit{(Equation 7.2)}$$

$$V_{Hybrid} = -9.0 \cdot 10^{-5} \cdot CC - 4.6 \cdot 10^{-3} \cdot FC + 1.2 \cdot FA - 0.2 \cdot EXP - 0.2 \cdot POW - 0.4 \qquad \textit{(Equation 7.3)}$$

$$V_{Fuelcell} = -9.0 \cdot 10^{-5} \cdot CC - 4.6 \cdot 10^{-3} \cdot FC + 1.2 \cdot FA - 0.2 \cdot EXP - 0.2 \cdot POW \qquad \textit{(Equation 7.4)}$$

Mode Choice Utility Formulations

$$V_{SOV} = -0.04 \cdot DT - 0.003 \cdot COST - 0.5 \qquad \textit{(Equation 7.5)}$$
$$V_{HOV} = -0.04 \cdot DT - 0.08 \cdot PDT - 0.003 \cdot COST - 0.5 \qquad \textit{(Equation 7.6)}$$
$$V_{Transit} = -0.04 \cdot DT - 0.08 \cdot WWT - 0.003 \cdot COST - 0.2 \cdot TRANSFERS - 0.5 \qquad \textit{(Equation 7.7)}$$
$$V_{Park\&Ride} = -0.04 \cdot DT - 0.08 \cdot WWT + -0.003 \cdot COST - 0.2 \cdot TRANSFERS - 2.0 \qquad \textit{(Equation 7.8)}$$
$$V_{Walk\&Cycle} = -0.04 \cdot DT + 0.2 \cdot PATH \qquad \textit{(Equation 7.9)}$$

Although highly significant and intuitive, the models were not without problems as the base line predictions did not match as well with reality as desired, and many of the segmentations based on different demographic variables were inconsistent. Two significant avenues were identified to explain these shortcomings in the model. First, only a limited number of attributes could be explored because of limitations in the experimental design. Based on the results of other survey questions and the literature, some of these excluded attributes would likely have influenced the decisions. Second, the utility models could have been better specified to allow error terms to be correlated across alternatives, or certain factors to have non-linear effects on utility. These alternate model formulations weren't explored because the basic forms were challenging enough to apply, and the broad scope of the experimental design didn't allow non-linear affects to be estimated. Although any of these extensions could have improved model validity, alternate approaches would have had their own limitations as well.

Before the discrete choice models could be incorporated into CIMS, two significant changes were needed. First, the park and ride alternative was removed from the mode choice model, and six additional vehicle types were added to the vehicle choice model. The mathematical properties of the discrete choice model facilitated these modifications, but error was inevitably introduced as alternative specific constants were assigned to the new technologies. Second, various versions of the alternative specific constants were designed for the vehicle choice model, because it seemed to have some significant (although explainable) divergences from reality. The modifiers for vehicle type availability were of some concern because they are large enough to dominate the other choice attributes. This dominance is quite likely accurate, but it points to the need to better understand how changes in availability affect consumer choice, which is handled very rudimentarily with the modifiers. To recognize the crudeness of this approach, any model predictions were made both with and without the modifiers.

7.2 Hybrid Modeling Today

In addition to the modifications made to the discrete choice models, two structural changes were made to CIMS to improve the way it represented transportation decisions. First, the original nested vehicle type node structure was modified so that all vehicle types competed directly in a single node. Second, capital costs were blocked from the market share allocation algorithm for mode choice to reflect the design of the discrete choice model. Currently this change has only been implemented external to the standard CIMS simulation procedures, but would ideally be programmed as an endogenous feature. Both changes have also just been made in the database used in this research, and it is strongly recommended that they be implemented in the standard version of CIMS so that they can be used in future research.

Once the changes were implemented, the performance of the discrete choice models was smoothly transferred to CIMS in a manner that limited changes to the existing parameters for the discount rate used in the decisions, the intangible costs of each technology, and the degree of market heterogeneity. The fit between the discrete choice models and CIMS were extremely satisfactory, although a perfect match is impossible because of fundamental differences in the mathematics of the market share curves. Although the lack of an exact fit isn't a serious issue, the same mathematical differences lead to potential problems in welfare costing and market share allocation when nested node structures are present in CIMS. Some suggestions for minimizing this error have been provided, but if additional DCM work is integrated with CIMS, the potential for error will continue to accumulate. Because of this concern, the decision to work with existing CIMS parameters instead of directly embedding the DCM utility formulations should be revisited in the future. Although there are clearly benefits to directly embedding the DCM's, this is by no means an easy decision because of the significant costs involved in changing the underlying structure to CIMS. Also, it is important to remember that CIMS has already been significantly improved in comparison with traditional top-down and bottom-up approaches, and that these additional improvements may not be that critical.

With the DCM's integrated into CIMS, the improved modeling capabilities were demonstrated with three policy simulations. In particular, a set of incentives for non-gasoline vehicle alternatives, and a similar set for non-single occupancy vehicles demonstrated the new types of policies that can now be simulated with CIMS. The results of these simulations confirmed the success of the integration exercise, because all of the simulations and their variations produced outcomes congruent with the underlying DCM's. They also demonstrated an ability to influence consumer decisions in mode and vehicle choice through both monetary and non-monetary policy. The simulations took advantage of the uncertainty that was quantified around the discrete choice models, which allowed CIMS outputs to be produced as probability distributions instead of point estimates. Although the initial time investment to develop the uncertainty curves was considerable, subsequent runs can now be produced in slightly more time than a single estimate CIMS run. This improvement over traditional CIMS outputs is a significant advancement because it provides explicit acknowledgement that predictions are uncertain, and that each possible outcome has a non-zero probability associated with it.

The steps described to this point have successfully improved the behavioral realism of a hybrid energy-economy model. Although a number of shortcomings have been identified throughout the process, none of these changes are required in the immediate future because the changes already implemented represent a significant improvement over the existing CIMS model. In comparison with the top-down approaches lacking technological detail, or bottom-up approaches failing to account for the reality of preferences, the improved version of CIMS represents a significant step forward in energy-economy modeling that is capable of much more sophisticated simulations to advise policy. All of the mentioned shortcomings were consciously omitted because they would have presented too many challenges for the scope of this research, and they were all deemed to be less significant than the issues already being addressed. That is not to say that they are not valuable steps forward in the development of hybrid models, but instead that they are only improvements on the significant progress that has already been made.

7.3 Hybrid Modeling Tomorrow

In addition to the already mentioned problems encountered in the research methodology, this section attempts to provide some broad directions for future research in hybrid energy-economy modeling, and CIMS in particular. All of these improvements are extensions of this work, and will likely need to either draw on multiple bodies of work, or become parts of longer-term research projects. As shown by some preliminary attempts to piece together different discrete choice models in this research, the first approach quickly opens up a vast wealth of potential modeling tools, but much of that information can be difficult to work through and can lead to inconsistent results. Looking at the other option, longer-term research would facilitate complete control of the research agenda, but it could also reduce research flexibility by charting a course too far into the future. The strengths and weaknesses of both approaches are not fully apparent at this juncture, and when any of the following agendas are pursued, both approaches should be given serious consideration. The four major avenues for future research are expanding the research scope, understanding the dynamics of emerging technologies, improving policy simulation flexibility, and continuing to quantify uncertainty.

Scope

The first avenue for improvement is probably the most important, and it would thankfully be able to draw upon all of the techniques and lessons learned in this research. Currently the scope of this research has been limited to mode and vehicle choice within personal urban transportation, and even when concurrent research in residential heating and industrial cogeneration is considered, a vast array of decisions could be better understood. Both within the transportation sector, and across other sectors, discrete choice models could be developed for other decisions and incorporated into CIMS to improve the overall realism of model predictions. For some of these decisions the DCM's developed in this research could probably be modified, but for the majority of them, the decisions characteristics are different enough to warrant additional research.

Dynamics of Emerging Technologies

The approach in this research took a broad view of a number of different technologies and attributes for mode and vehicle type choice, and although valuable, it made it impossible to garner a detailed understanding of any single attribute or technology. This detailed understanding is exactly what is required to effectively simulate the innovation and adoption of emerging technologies. For example, this research looked at two levels of fuel availability and assumed a linear response to all other levels, where in reality consumers have been found to be much more interested in fuel availability at low levels and there is probably a threshold below which they are unwilling to buy a vehicle. These types of detailed dynamics are commonplace in new technologies, and to successfully address them, one or two specific policy levers needs to be selected for detailed study.

Policy Simulation Challenges

Despite the fact that this research has offered some interesting policy simulations, they are by no means comprehensive analyses, and in order to properly compare different policy options, the work needs to be extended in three ways. First, costs were excluded from the presentation of results because the costs associated with the different policies were not available. This has not been a problem in the past, because CIMS has primarily been used to model taxes, which are re-distributive (i.e. zero financial costs unless changes in technology choices are induced) policies with the exception of the administrative costs. For the infrastructure investments involved in many transportation policies, the policy costs are far from negligible, and some estimate would need to be tied to a policy scenario before the costs could be estimated. Without this, investments in transit, or subsidizing fuel availability would seem like win-win options because they would be making more environmentally benign forms of transportation more attractive at apparently zero cost. This is not a limitation of CIMS, because once costing estimates are obtained for various policies, they could easily be included in any financial or welfare cost calculations.

A second limitation, which is closely tied to the current CIMS setup, is the limited ability to model non-monetary policies that change through time. Policies that include changing targets for stocks or shares in each period (such as vehicle emissions standards) can be simulated, but any of the new non-monetary variables introduced in this research can't currently be changed through the course of a simulation. Once values for the intangible costs are selected, they are fixed for all periods of the simulation. This is probably the most straightforward of all the enhancements discussed in this section because it could be simply accomplished by adding an intangible cost field to CIMS for each period instead of using a single value. Despite the simplicity, it would open up a broad range of policy options for simulation including examples such as steadily increasing investments in transit service, or increasing fuel availability for non-gasoline vehicles. Being able to simulate these types of policies would be beneficial because they are much more representative of the marginal changes that are likely to take place in reality.

Even with these two extensions, effectively modeling transportation policy will be challenging with CIMS because of the spatial element involved in many transportation policies. More specifically, it will always be difficult to relate the impact of an actual policy to a change in an attribute value in the discrete choice model, which would be translated into CIMS. Examples of this challenge include trying to figure out what attribute values to use for time to reflect a new carpooling lane on a city's major expressway, or determining the appropriate change in cost to reflect a toll to enter a city's downtown core. These types of policy would change the traveling time or cost for some commuters, but the impact would be negligible for those who don't use the affected roads. CIMS is a geographically aggregated model, meaning that it doesn't account for spatial differences (other than regions), so physical quantities such as roads and highways, and the cities and neighborhoods they connect are not considered, which makes simulating policies tied to these physical boundaries extremely problematic. Even if the average effect of a policy could be determined for an entire CIMS region, a second problem is that there is no guarantee that applying the average value to the entire population is equivalent to focusing the full effect on a subset of the population. Based on DCM's developed in this research the two approaches will yield identical results, but only because the attributes have all been assumed to have linear effects on utility. If more complicated utility functions were explored and the relationships were found to be non-linear, additional approaches would need to be considered. A possible future approach for dealing with this problem would be linking CIMS with more disaggregated transportation model for the major urban centers in Canada. The exact details of such an approach are beyond the scope of this research, but based on the recommendations resulting from Tisdale's (2003) work with CIMS on the effect of air contaminants at a local scale, such an approach shows promise.

Uncertainty

Throughout this paper, the uncertainty surrounding model predictions has been an ongoing focus because of its importance in illuminating confidence in predictions, facilitating comparisons between predictions, and helping decide between alternative actions. The benefits of including uncertainty in any analysis should never be undervalued, but it is also important to recognize that the analysis in this paper has focused on a single source of uncertainty. By limiting the consideration of uncertainty to the behavioral aspects of personal urban transportation decision, the challenge has been made tractable, but the omitted portions should not be forgotten. Possibly just as important is the uncertainty present in technical estimates, such as the base stocks, costs, and emissions factors needed to make CIMS a technologically explicit model. Each of these quantities represents an amalgamation of a variety of similar technologies and the values have been estimated to reflect the average for the range that exists across the country. Because the technical figures in CIMS' transportation model were updated for the National Climate Change Implementation Process the mean estimates are probably quite accurate, but the data resulting from the process did not explicitly account for uncertainty. Until this source of uncertainty is investigated as thoroughly as the behavioral component, the magnitude by which the uncertainty estimates under-present the range value won't be known.

These four major avenues, scope, the dynamics of emerging technology, policy simulation challenges, and uncertainty, all represent significant steps forward for CIMS, or any model for that matter. Returning to the top-down / bottom-up debate again however, none of these improvements are required to bridge the gap in modeling philosophies. They all represent improvements to what is already a hybrid model according to the definition used in this paper. With that perspective, it may be more useful to take a step back to examine the current improvements and gain as much from them before moving onto new challenges. This approach will allow the new capabilities to be fully tested and exploited, and in addition to the valuable policy analysis that can be done during this process, new avenues for improvements will also probably be identified.

Appendix 1 – Ethics Approval

APPENDIX A*

S I M O N   F R A S E R
U N I V E R S I T Y

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

May 20, 2003

Mr. Matt Horne
Graduate Student
School of Resource and
Environmental Management
Simon Fraser University

Dear Mr. Horne:

Re: Incorporating Personal Urban Transportation Perferences into an Integrated Energy Economy Model
"Assessing Parameter Uncertainty in Technology Specific, Integrated"
Office of Energy Efficiency

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

Sincerely,

Dr. Hal Weinberg, Director
Office of Research Ethics

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

APPENDIX 2 – SURVEY INSTRUMENTS

Phone Script (3 Pages)

Hello, my name is _______________ calling on behalf of Simon Fraser University. We are conducting a survey to learn about Canadians' attitudes and preferences toward personal transportation. Your answers will be used to help Canadian cities set their transportation priorities, and shape future transportation policies across Canada.

The survey is composed of a five minute phone interview, and a twenty minute follow-up mail questionnaire. For each completed mail survey, we will donate one dollar to Unicef.

IF NECESSARY READ:
I am not selling anything, and all of your responses will be kept confidential.

Part A – Recruitment

1. ***Are you, or someone else in your household who is 18 years of age or older interested in participating in this survey?***
    1. Yes
    2. No SKIP TO Q13

2. ***Thank you. Before we continue, may I confirm that you are 18 years of age or older?***
    1. Yes
    2. No THANK AND TERMINATE WITH REJECTION REASON 1

Part B – Vehicle Ownership

3. Do you own or have access to a vehicle?
    1. Yes
    2. No SKIP TO Q6.

4. What type of vehicle do you use most often,
   READ LIST
    1. A compact car (such as Honda Civic, Toyota Corolla, or Chevy Cavalier),
    2. a mid-size car (such as Ford Taurus, Toyota Camry, or Honda Accord),
    3. a full-size car (such as Ford Crown Victoria, Chrysler Concord, or Lincoln Town Car),
    4. a Pickup Truck,
    5. a Minivan,
    6. a SUV/ (Sport Utility Vehicle), or
    7. a motorcycle?
    8. DON'T KNOW/REFUSED

5. How much did this vehicle cost when it was purchased (the vehicle you most commonly use)?

   ____

   999999. DON'T KNOW/ REFUSED

Part C – Commuting

6. Do you commute to work or school at least once per week?
    1. Yes
    2. No

IF Q6=2 AND Q3=2 THANK AND TERMINATE WITH REJECTION REASON 2

IF Q6=2 SKIP TO Q11

7. How do you most commonly commute to work or school?
   READ LIST IF NECESSARY
   ALLOW MULTIPLE RESPONSES

   1. driving alone (SOV),
   2. carpooling,
   3. public transit,
   4. walking, or
   5. cycling?

8. On average, approximately how many minutes does it take you to travel one-way between home and work or school when *<driving alone / carpooling / taking transit / walking / cycling>*? __________

9. Approximately how many kilometers is your one-way trip from home to work or school?
   IF DK – ASK FOR BEST GUESS

   ____

   999999. DON'T KNOW

If Q7<>1, 2 or 3 SKIP TO Q11.

10. On average, approximately how much do you spend on commuting costs when *<<driving alone / carpooling / taking transit>>* to work or school?

IF COMMON COMMUTING MODE IS DRIVING ALONE OR CARPOOLING:

Please only consider gas, parking and road toll expenses, and feel free to give your answer on a weekly or monthly basis; whichever is easier.

IF COMMON MODE IS TAKING TRANSIT:

Please only consider transit fares, and feel free to give your answer on a weekly or monthly basis; whichever is easier.

____

999999. DON'T KNOW / REFUSED

Part D - Prepare for Mail Portion of Survey

That completes the phone portion of this survey. The second half of the survey will be sent to you by mail within the next week.

11. May I please have your complete address in order to mail the next portion of the survey?
    ADDRESS:
    CITY:
    PROVINCE:
    POSTAL CODE:

12. Finally, what name would you like to appear on the mailing label?
    FIRST NAME:
    LAST NAME:

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

Part E – Rejection Information

13. Before you go, could you please tell me why you aren't willing to participate in this study?
    1. Not interested,
    2. Don't know enough about transportation issues,
    3. Don't have time,
    4. Other,

5. Prefer not to say/ REFUSED

Rejection Reason 1: I'm sorry, but Simon Fraser University ethical regulations restrict us from interviewing anyone under the age of 18. Thank you for your time.

Rejection Reason 2: I'm sorry, but because you don't have access to a vehicle, and don't commute at least once per week, you don't qualify for the remainder of this survey. Thank you for your time.

Cover Letter 1 (1 Page)

Simon Fraser University

School of Resource and Environmental Management | Burnaby, BC, V5A 1S6
Department: 604.291.4659
Survey: 604.268.6621

15-Sep-03

«First_Name» «Last_Name»,

As a follow up to our recent telephone contact, please find enclosed your copy of the Canadian Transportation Preferences Survey. We appreciate your help with this important research, and your input will help us understand how Canadians perceive and utilize the transportation systems in their communities. The results of the study will help us pinpoint current strengths and weaknesses, which we can use to predict how transportation patterns will evolve under various policy and investment strategies.

Your answers are completely confidential, and will only be released as summaries in which no individual's answers can be identified. When you return your completed questionnaire, your name will be deleted from the mailing list, and never connected to your answers in any way. Your participation is entirely voluntary, and we will assume that by completing and returning this survey you are indicating your consent to participate in this research. Please note that Simon Fraser University ethical regulations require you to be 18 or older to complete this survey. If you are not 18 or older, or if you decide for some reason not to complete the survey, please return it unanswered in the enclosed envelope.

We can't stress how grateful we are that you are willing to contribute to this study, and as a small token of our gratitude, please accept the enclosed $1 coin. Also, for each survey returned to us, we will donate an additional $1 to Unicef.

If you have any questions or concerns about this research we would be glad to talk to you. Please direct questions or concerns about the survey to the primary researcher, Matthew Horne, by phone at 604.268.6621 or via email to mhorne@sfu.ca. All messages will be returned the next day. More general concerns about the research can be directed to Frank Gobas at 604.291.4659.

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

Sincerely,

Matthew Horne
Graduate Student Researcher
School of Resource and Environmental Management

Survey (16 Pages)

Simon Fraser
University

CANADIAN TRANSPORTATION PREFERENCES STUDY

Energy and
Materials
Research Group

Thank you for agreeing to participate in our survey. This information will be used to analyze the transportation choices available to Canadians today and in the future. Remember that with each received survey, we will donate $1 to Unicef. Your opinions and ideas are important, so please answer each question. The following sample illustrates the format that will be used for questions in the survey.

Sample Question

Question Number | Question (plain text) | Instructions (italicized)

1. How satisfied are you with these features of public transit in your city? *Please indicate your opinion for each feature.*

	Level of Satisfaction With Public Transit					
	Very Dissatisfied	←	Neutral	→	Very Satisfied	Don't Know
Frequency of Service	☑	☐	☐	☐	☐	☐
Cleanliness of vehicles	☐	☐	☑	☐	☐	☐
Friendliness of drivers	☐	☐	☐	☑	☐	☐
Timeliness of arrivals	☐	☐	☑	☐	☐	☐

Public Transit Features | Your Answers

The survey should take approximately 25 minutes to complete.

Part 1 – Your Transportation Options, Requirements and Habits

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

   ☐ None } ⇨ *If none, please skip to question 8.*
   ☐ One
   ☐ Two
   ☐ Three or more } ⇨ *If one or more, please continue to question 2.*

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

   Make: ____________ *(Ford for example)* Model: ____________ *(Explorer for example)* Year: ____________

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

   ____________ years

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

   ______________ years

5. What are the annual maintenance costs for this vehicle?

   - ❑ Less than $1,000 per year
   - ❑ $1,000 to $2,000 per year
   - ❑ $2,001 to $3,000 per year
   - ❑ More than $3,000 per year
   - ❑ Don't know

6. What importance did the following factors have in your family's decision to purchase this vehicle? *Please indicate the importance you place on each factor.*

	Importance of Factor in Vehicle Purchase Decision					
	Not at All Important		Somewhat Important		Very Important	Don't Know
Purchase Price	❑	❑	❑	❑	❑	❑
Vehicle Type	❑	❑	❑	❑	❑	❑
Fuel Economy	❑	❑	❑	❑	❑	❑
Horsepower	❑	❑	❑	❑	❑	❑
Safety	❑	❑	❑	❑	❑	❑
Seating Capacity	❑	❑	❑	❑	❑	❑
Reliability	❑	❑	❑	❑	❑	❑
Appearance and Styling	❑	❑	❑	❑	❑	❑
Other: ______________	❑	❑	❑	❑	❑	❑

7. Considering your transportation requirements, do you think your family could meet its needs with fewer vehicles, either by travelling less, or using different methods of transportation?

   - ❑ Yes
   - ❑ No

8. How many people in your family travel to work or school at least three times per week?

   - ❑ None
   - ❑ One
   - ❑ Two
   - ❑ Three or more

9. Do **you** travel to work or school at least once per week?

- ❑ Yes ⇨ *If yes, please continue to question 10.*
- ❑ No ⇨ *If no, please skip to question 18.*

10. On average, how long would it take you to travel from home to work or school by each of the following methods? ***Please check the best response for each method.***

	Travel Time to Work or School						
	Under 20 Minutes	21 to 40 Minutes	41 to 60 Minutes	61 to 90 Minutes	Over 90 Minutes	Not Available	Don't know
Vehicle: Alone	❑	❑	❑	❑	❑	❑	❑
Vehicle: Carpool	❑	❑	❑	❑	❑	❑	❑
Public Transit	❑	❑	❑	❑	❑	❑	❑
Park and Ride	❑	❑	❑	❑	❑	❑	❑
Cycling	❑	❑	❑	❑	❑	❑	❑
Walking	❑	❑	❑	❑	❑	❑	❑
Other: ____________	❑	❑	❑	❑	❑	❑	❑

11. On average, how many times per week do you travel from home to work or school using each of the following methods? *Please check the best response for each method.*

	Times per week					
	None	One	Two	Three	Four	Five or more
Vehicle: Alone	❑	❑	❑	❑	❑	❑
Vehicle: Carpool	❑	❑	❑	❑	❑	❑
Public Transit	❑	❑	❑	❑	❑	❑
Park and Ride	❑	❑	❑	❑	❑	❑
Cycling	❑	❑	❑	❑	❑	❑
Walking	❑	❑	❑	❑	❑	❑
Other: ____________	❑	❑	❑	❑	❑	❑

12. Does the pattern you just described change throughout the year?

- ❑ Yes ⇨ *If yes, please explain.* ______________________________
- ❑ No

13. What importance do the following factors have in your decision between different methods of travel? *Please indicate the importance you place on each factor.*

	Importance of Factor in Travel Method Decision: Not at All Important		Somewhat Important		Very Important	Don't Know
Cost	❑	❑	❑	❑	❑	❑
Travel Time	❑	❑	❑	❑	❑	❑
Comfort	❑	❑	❑	❑	❑	❑
Flexibility	❑	❑	❑	❑	❑	❑
Safety	❑	❑	❑	❑	❑	❑
Privacy	❑	❑	❑	❑	❑	❑
Environmental Impact	❑	❑	❑	❑	❑	❑
Reliability	❑	❑	❑	❑	❑	❑
Availability of Method	❑	❑	❑	❑	❑	❑
Other: ________________	❑	❑	❑	❑	❑	❑

14. In an average week, what proportion of your personal total travelling time is spent commuting to work or school? *Please consider all of your travelling needs including commuting, running errands, shopping, visiting family and friends, and entertainment.*

❑ Less than 25%
❑ 25% to 50%
❑ More than 50%

15. Regarding your commute to work or school, do you have the option of using the following services? *Please indicate the availability of each transportation service.*

	Yes, Available	No, Not Available	Don't Know
Bringing bicycles on public transit	❑	❑	❑
Using bike routes or paths	❑	❑	❑
Showering and changing at work or school	❑	❑	❑
Driving in carpooling lanes	❑	❑	❑
Riding express buses or rapid transit	❑	❑	❑
Using a carpool coordinating service	❑	❑	❑
Driving on express toll roads	❑	❑	❑

16. How many days a week do you think your job or education could be completed from home?

- ☐ None
- ☐ One or Two
- ☐ Three or Four
- ☐ Five or more
- ☐ Don't know

17. Considering your current commute, how many days a week would you work from home if you had an employer or school that gave you the option of working from home?

- ☐ None
- ☐ One or Two
- ☐ Three or Four
- ☐ Five or more
- ☐ Don't know

18. Do you have friends or co-workers who use the following transportation methods or types of vehicles as their primary means of commuting to work or school? *Please check one answer for each transportation method and vehicle type.*

	Yes	No	Don't Know
Carpooling	☐	☐	☐
Public Transit	☐	☐	☐
Walking	☐	☐	☐
Cycling	☐	☐	☐
Hybrid electric vehicle (such as the Honda Insight)[39]	☐	☐	☐
Alternative fuel vehicle (using natural gas for example)[40]	☐	☐	☐

19. Do you have any comments on the answers you provided in this section of the survey?

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[39] Hybrid electric vehicles such as the Honda Insight and Toyota Prius combine gasoline and electric systems.
[40] Alternative fuel vehicles use fuels other than gasoline or diesel, such as natural gas, ethanol, and propane.

Part 2 – Your Vehicle Preferences

This section presents four hypothetical choices, each asking you to choose between four vehicles. For each choice, read over the attributes, and indicate the vehicle you would prefer. Imagine that all four vehicles are <<compact cars/mid-size cars/full-size cars/trucks/vans/SUVs>>

Important Concepts

- *Alternative Fuel Vehicle – Powered using fuels other than gasoline or diesel, such as natural gas, ethanol, and propane.*
- *Hybrid Electric Vehicle – Powered using a combination of gasoline and electric systems.*
- *Hydrogen Fuel Cell Vehicle – Powered using hydrogen fuel, producing water as exhaust. Anticipated release date of 2004.*
- *Express Lane Access – Scenario where vehicles with lower emissions would be given access to express lanes on major roads. Assume a time savings of 20% when lanes are available.*

20. If these were the only four vehicles available to you, which would you choose?

Vehicle Type	***Gasoline Vehicle***	***Alternative Fuel Vehicle***	***Hybrid-Electric Vehicle***	***Hydrogen Fuel Cell Vehicle***
Purchase Price	$45,000	$45,000	$45,000	$45,000
Fuel Cost	$10/week	$10/week	$10/week	$10/week
Stations with Proper Fuel	100%	100%	100%	100%
Express Lane Access	None	None	None	None
Emissions Compared to Current Vehicle	Equal	25% Less	Equal	100% Less
Power Compared to Current Vehicle	Equal	Equal	25% Less	10% Less
	☐	☐	☐	☐

21. If these were the only four vehicles available to you, which would you choose?

Vehicle Type	***Gasoline Vehicle***	***Alternative Fuel Vehicle***	***Hybrid-Electric Vehicle***	***Hydrogen Fuel Cell Vehicle***
Purchase Price	$45,000	$45,000	$45,000	$45,000
Fuel Cost	$10/week	$10/week	$10/week	$10/week
Stations with Proper Fuel	100%	100%	100%	100%
Express Lane Access	None	None	None	None
Emissions Compared to Current Vehicle	Equal	25% Less	Equal	100% Less
Power Compared to Current Vehicle	Equal	Equal	25% Less	10% Less
	☐	☐	☐	☐

22. If these were the only four vehicles available to you, which would you choose?

Vehicle Type	*Gasoline Vehicle*	*Alternative Fuel Vehicle*	*Hybrid-Electric Vehicle*	*Hydrogen Fuel Cell Vehicle*
Purchase Price	$45,000	$45,000	$45,000	$45,000
Fuel Cost	$10/week	$10/week	$10/week	$10/week
Stations with Proper Fuel	100%	100%	100%	100%
Express Lane Access	None	None	None	None
Emissions Compared to Current Vehicle	Equal	25% Less	Equal	100% Less
Power Compared to Current Vehicle	Equal	Equal	25% Less	10% Less
	❑	❑	❑	❑

23. If these were the only four vehicles available to you, which would you choose?

Vehicle Type	*Gasoline Vehicle*	*Alternative Fuel Vehicle*	*Hybrid-Electric Vehicle*	*Hydrogen Fuel Cell Vehicle*
Purchase Price	$45,000	$45,000	$45,000	$45,000
Fuel Cost	$10/week	$10/week	$10/week	$10/week
Stations with Proper Fuel	100%	100%	100%	100%
Express Lane Access	None	None	None	None
Emissions Compared to Current Vehicle	Equal	25% Less	Equal	100% Less
Power Compared to Current Vehicle	Equal	Equal	25% Less	10% Less
	❑	❑	❑	❑

24. Do you have any comments on the choices you made in this section of the survey?

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Part 3 – Your Transportation Mode Preferences

This section presents four hypothetical situations, each asking you to choose between four options for getting to work or school. For each question, read over the attributes, and indicate which method you would prefer. You can assume that all of the methods are available to you (even if you don't have access to a car for example). Please consider all other commuting constraints you might have when making your decision.

Important Concepts

- *Park and Ride – Parking at a transit station and taking transit to work from there.*
- *Cycle or Walk – Please select this choice if you prefer the cycling or the walking option.*

25. If these were the only methods available to get to work or school, which would you choose?

Vehicle: Alone	*Vehicle: Carpool*	*Public Transit*	*Park and Ride*
Total Travel Time: 20 minutes	Total Travel Time: 20 minutes	Total Travel Time: 20 minutes	Total Travel Time: 20 minutes
	Pickup / Drop-off Time: 5 minutes	Walking / Waiting Time: 5 minutes	Walking / Waiting Time: 5 minutes
Cost: \$10 per week	Cost: \$10 per week	Cost: \$10 per week	Cost: \$10 per week
		Transfers Required: One	Transfers Required: None
☐	☐	☐	☐

26. If these were the only methods available to get to work or school, which would you choose?

Vehicle: Alone	*Vehicle: Carpool*	*Public Transit*	*Walk or Cycle*
Total Travel Time: 20 minutes	Total Travel Time: 20 minutes	Total Travel Time: 20 minutes	Total Travel Time: 20 or 30 minutes
	Pickup/Drop-off Time: 5 minutes	Walking / Waiting Time: 5 minutes	
Cost: \$10 per week	Cost: \$10 per week	Cost: \$10 per week	Cost: \$0 per week
		Transfers Required: One	Cycling Conditions: On road or On path
☐	☐	☐	☐

27. If these were the only methods available to get to work or school, which would you choose?

Vehicle: Alone	*Vehicle: Carpool*	*Public Transit*	*Park and Ride*
Total Travel Time: 20 minutes	Total Travel Time: 20 minutes	Total Travel Time: 20 minutes	Total Travel Time: 20 minutes
	Pickup / Drop-off Time: 5 minutes	Walking / Waiting Time: 5 minutes	Walking / Waiting Time: 5 minutes
Cost: \$10 per week	Cost: \$10 per week	Cost: \$10 per week	Cost: \$10 per week
		Transfers Required: One	Transfers Required: None
☐	☐	☐	☐

28. If these were the only methods available to get to work or school, which would you choose?

Vehicle: Alone	*Vehicle: Carpool*	*Public Transit*	*Walk or Cycle*
Total Travel Time: 20 minutes	Total Travel Time: 20 minutes	Total Travel Time: 20 minutes	Total Travel Time: 20 or 30 minutes
	Pickup/Drop-off Time: 5 minutes	Walking / Waiting Time: 5 minutes	
Cost: \$10 per week	Cost: \$10 per week	Cost: \$10 per week	Cost: \$0 per week
		Transfers Required: One	Cycling Conditions: On road or On path
☐	☐	☐	☐

29. Do you have any comments on the choices you made in this section of the survey?

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Part 4 – Your Views on Transportation Issues

30. What is your level of support/opposition for the following government actions that would influence your transportation system? *Please check the best answer for each group of actions.*

	Your Degree of Support: Strongly Opposed		Neutral		Strongly Supportive	Don't Know
Improving traffic flow by building new roads, and expanding existing roads.	❑	❑	❑	❑	❑	❑
Discouraging automobile use with road tolls, gas taxes, and vehicle surcharges.	❑	❑	❑	❑	❑	❑
Making neighborhoods more attractive to walkers and cyclists using bike lanes, and speed controls.	❑	❑	❑	❑	❑	❑
Reducing vehicle emissions with regular testing, and manufacturer emissions standards.	❑	❑	❑	❑	❑	❑
Making carpooling and transit faster by giving them dedicated traffic lanes, and priority at intersections.	❑	❑	❑	❑	❑	❑
Making transit more attractive by reducing fares, increasing frequency, and expanding route coverage.	❑	❑	❑	❑	❑	❑
Reducing transportation distances by promoting mixed commercial and residential, and high-density development.	❑	❑	❑	❑	❑	❑
Reducing transportation needs by encouraging compressed workweeks and working from home.	❑	❑	❑	❑	❑	❑

31. Do you have any comments regarding the actions discussed in question 30?

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32. How do you feel about the role governments plays in shaping your transportation system?

- ❑ They are doing too much.
- ❑ They are doing about the right amount.
- ❑ They aren't doing enough.
- ❑ Don't know

33. Thinking about your daily experiences, how serious do you consider the following problems related to transportation to be? *Please indicate your opinion for each potential problem.*

	Seriousness of Problem					
	Not a Problem		Minor Problem		Major Problem	Don't Know
Traffic congestion you experience while driving.	❑	❑	❑	❑	❑	❑
Traffic noise you hear at home, work, or school.	❑	❑	❑	❑	❑	❑
Vehicle emissions, which impact local air quality.	❑	❑	❑	❑	❑	❑
Accidents caused by aggressive or absent minded drivers.	❑	❑	❑	❑	❑	❑
Vehicle emissions, which contribute to global warming.	❑	❑	❑	❑	❑	❑
Unsafe communities due to speeding traffic.	❑	❑	❑	❑	❑	❑

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

	Compared to a Gasoline Vehicle					
	Much Worse	Slightly Worse	Equal	Slightly Better	Much Better	Don't Know
Impact on the Environment	❑	❑	❑	❑	❑	❑
Reliability	❑	❑	❑	❑	❑	❑
Refueling Time	❑	❑	❑	❑	❑	❑
Distance per Fill-up	❑	❑	❑	❑	❑	❑
Horsepower and Acceleration	❑	❑	❑	❑	❑	❑
Fuel Costs	❑	❑	❑	❑	❑	❑
Purchase Price	❑	❑	❑	❑	❑	❑

35. Are you satisfied with the selection of hybrid electric vehicles available in the market?

❑ Yes
❑ No
❑ Don't Know

⇨ *Please explain.* ________________________________

36. How do you believe carpooling, taking transit, walking, and cycling each compare with driving alone on each of the following criteria? *Please indicate your opinion for each transportation method.*

		Comparison with Driving Alone					
		Much Worse	Slightly Worse	Equal	Slightly Better	Much Better	Don't Know
Safety while travelling	Carpooling	❑	❑	❑	❑	❑	❑
	Public Transit	❑	❑	❑	❑	❑	❑
	Walking	❑	❑	❑	❑	❑	❑
	Cycling	❑	❑	❑	❑	❑	❑
Comfort	Carpooling	❑	❑	❑	❑	❑	❑
	Public Transit	❑	❑	❑	❑	❑	❑
	Walking	❑	❑	❑	❑	❑	❑
	Cycling	❑	❑	❑	❑	❑	❑
Impact on the Environment	Carpooling	❑	❑	❑	❑	❑	❑
	Public Transit	❑	❑	❑	❑	❑	❑
	Walking	❑	❑	❑	❑	❑	❑
	Cycling	❑	❑	❑	❑	❑	❑
Flexibility	Carpooling	❑	❑	❑	❑	❑	❑
	Public Transit	❑	❑	❑	❑	❑	❑
	Walking	❑	❑	❑	❑	❑	❑
	Cycling	❑	❑	❑	❑	❑	❑

37. How satisfied are you with the following features of the public transit system in your city? *Please indicate your opinion for each transit feature.*

	Satisfaction with Public Transit					
	Very Dissatisfied		Neutral		Very Satisfied	Don't Know
Location of bus stops	❑	❑	❑	❑	❑	❑
Frequency of bus service	❑	❑	❑	❑	❑	❑
Timeliness of bus service	❑	❑	❑	❑	❑	❑
Availability of seats	❑	❑	❑	❑	❑	❑
Cleanliness of vehicles	❑	❑	❑	❑	❑	❑
Convenience of bus routes	❑	❑	❑	❑	❑	❑
Cost of fares	❑	❑	❑	❑	❑	❑

38. Do you have any comments on the answers you provided in this section of the survey?

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Part 5 - Additional Information About Yourself

39. What is your gender?

- ❑ Female
- ❑ Male

40. How many people live in your family household?

- ❑ One
- ❑ Two
- ❑ Three
- ❑ Four or more

41. In 2001, which category best described your total family income, before tax?

- ❑ $20,000 or less
- ❑ $20,001 to $40,000
- ❑ $40,001 to $60,000
- ❑ $60,0001 to $80,000
- ❑ $80,001 or over

42. What type of dwelling do you live in?

- ❑ Single-family detached house
- ❑ Duplex, townhouse or row house
- ❑ Apartment building
- ❑ Other: ______________________________

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

- ❑ Less than Grade 9
- ❑ Grade 9
- ❑ Grade 12
- ❑ College, CEGEP or other post-secondary diploma
- ❑ University

44. What is your age?

- ☐ 25 years or less
- ☐ 26 to 40 years
- ☐ 41 to 55 years
- ☐ 56 years or older

45. What is your current occupation?

____

46. Do you work at the same location most days?

- ☐ Yes
- ☐ No ⇨ *If no, please explain.* _______________________________________

47. Do you work the same hours most days?

- ☐ Yes
- ☐ No ⇨ *If no, please explain.* _______________________________________

48. Do you have any comments on the answers you provided in this section of the survey?

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If you have any questions about this survey, or the research in general, please contact the primary researcher, Matt Horne.

Phone: 604.268.6621
Email: mhorne@sfu.ca

If you would like to speak to a representative of the School of Resource and Environmental Management, please contact the director, Frank Gobas.

Phone: 604.291.4659

Once you have completed this survey, please return it in the accompanying stamped envelope to the following address:

Canadian Transportation Preferences Study
EMRG/CIEEDAC
Room 2123 East Academic Annex
Simon Fraser University
8888 University Drive
Burnaby, BC, V5A 1S6

If you would like to see the results of this study, updates will be regularly posted at the following website:

http://www.emrg.sfu.ca/transportation

Thank you again for taking the time to offer us your ideas on these important issues.

Followup Postcard (1 Page)

«First Name» «Last Name»,

Two weeks ago you were sent your copy of the Canadian Transportation Preferences Survey as a follow-up to our phone interview on «Respondant_Date».

If you have already completed and returned the survey, we want to express our appreciation for your help with this research project. If not, please do so today. We are especially grateful for your help because it is only by asking people like you to share your experiences that we can understand how Canadians view their transportation systems.

If you didn't receive your copy of the survey, or if you have misplaced it, please contact us and we will send you a replacement immediately. You can leave a message by telephone at 604.268.6621, or by email at mhorne@sfu.ca.

Thank you again for your participation in this project.

Sincerely,

Matthew Horne

Cover Letter 2 (1 Page)

Simon Fraser University

School of Resource and Environmental Management   Burnaby, BC, V5A 1S6
Department Phone: 604.291.4659
Survey Phone: 604.268.6621

15-Sep-03

«First_Name» «Last_Name»,

About four weeks ago we sent you your copy of the Canadian Transportation Preferences Survey. To the best of our knowledge, it hasn't been returned as of 15-Nov-02. The study is drawing to a close, and this is the last contact that will be made to the people who were contacted by phone in early October.

Individuals from across the country who have already returned their surveys have responded with strong opinions on the state of their transportation systems and how they feel they can be improved. As well, they have provided a wealth of information on their commuting patterns and vehicle purchasing preferences. The results of the survey will provide a clear picture of the Canadians' opinions and preferences, and will be very useful for both transportation planning and energy use research.

We are sending this final contact because we are concerned that people who have not yet responded may have experiences with their transportation system that differ from those who have already replied. Hearing from everyone initially contacted helps ensure that the results are as accurate as possible and reflect the broad range of opinions found across Canada.

If you have any questions about the survey or research, please leave a message by phone at 604.268.6621 or by email to mhorne@sfu.ca. Both the voice mail and email are checked daily and any messages will be returned the next day.

As a reminder, all of your answers are completely confidential, and they will only be released as summaries in which no individual's answers can be identified. When you return your completed questionnaire, your name will be deleted from the mailing list, and never connected to your answers in any way.

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

Thank you for your time and assistance.

Sincerely,

Matthew Horne
Primary Researcher,
School of Resource and Environmental Management

APPENDIX 3 – EXPERIMENTAL DESIGN

Basic 2^{16-11} Experimental Design

		Attribute															
		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
Choice Profile	1	-1	-1	-1	-1	-1	-1	-1	-1	1	1	1	1	1	1	1	1
	2	1	-1	-1	-1	1	1	1	-1	-1	-1	-1	-1	1	1	1	1
	3	-1	1	-1	-1	1	1	-1	1	-1	-1	1	1	-1	-1	1	1
	4	1	1	-1	-1	-1	-1	1	1	1	1	-1	-1	-1	-1	1	1
	5	-1	-1	1	-1	1	-1	1	1	-1	1	-1	1	-1	1	-1	1
	6	1	-1	1	-1	-1	1	-1	1	1	-1	1	-1	-1	1	-1	1
	7	-1	1	1	-1	-1	1	1	-1	1	-1	-1	1	1	-1	-1	1
	8	1	1	1	-1	1	-1	-1	-1	-1	1	1	-1	1	-1	-1	1
	9	-1	-1	-1	1	-1	1	1	1	-1	1	1	-1	1	-1	-1	1
	10	1	-1	-1	1	1	-1	-1	1	1	-1	-1	1	1	-1	-1	1
	11	-1	1	-1	1	1	-1	1	-1	1	-1	1	-1	-1	1	-1	1
	12	1	1	-1	1	-1	1	-1	-1	-1	1	-1	1	-1	1	-1	1
	13	-1	-1	1	1	1	1	-1	-1	1	1	-1	-1	-1	-1	1	1
	14	1	-1	1	1	-1	-1	1	-1	-1	-1	1	1	-1	-1	1	1
	15	-1	1	1	1	-1	-1	-1	1	-1	-1	-1	-1	1	1	1	1
	16	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	17	1	1	1	1	1	1	1	1	-1	-1	-1	-1	-1	-1	-1	-1
	18	-1	1	1	1	-1	-1	-1	1	1	1	1	1	-1	-1	-1	-1
	19	1	-1	1	1	-1	-1	1	-1	1	1	-1	-1	1	1	-1	-1
	20	-1	-1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	-1	-1
	21	1	1	-1	1	-1	1	-1	-1	1	-1	1	-1	1	-1	1	-1
	22	-1	1	-1	1	1	-1	1	-1	-1	1	-1	1	1	-1	1	-1
	23	1	-1	-1	1	1	-1	-1	1	-1	1	1	-1	-1	1	1	-1
	24	-1	-1	-1	1	-1	1	1	1	1	-1	-1	1	-1	1	1	-1
	25	1	1	1	-1	1	-1	-1	-1	1	-1	-1	1	-1	1	1	-1
	26	-1	1	1	-1	-1	1	1	-1	-1	1	1	-1	-1	1	1	-1
	27	1	-1	1	-1	-1	1	-1	1	-1	1	-1	1	1	-1	1	-1
	28	-1	-1	1	-1	1	-1	1	1	1	-1	1	-1	1	-1	1	-1
	29	1	1	-1	-1	-1	-1	1	1	-1	-1	1	1	1	1	-1	-1
	30	-1	1	-1	-1	1	1	-1	1	1	1	-1	-1	1	1	-1	-1
	31	1	-1	-1	-1	1	1	1	-1	1	1	1	1	-1	-1	-1	-1
	32	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

Profiles Within Each Choice Set

Choice Set	Choice 1 Profile Number	Choice 2 Profile Number	Choice 3 Profile Number	Choice 4 Profile Number
1	4	31	3	1
2	24	8	23	12
3	5	27	6	9
4	25	21	13	28
5	20	7	22	19
6	17	30	16	14
7	32	11	18	10
8	2	26	29	15
9	4	24	5	25
10	20	17	32	2
11	31	8	27	21
12	7	30	11	26
13	3	23	6	13
14	22	16	18	29
15	1	12	9	28
16	19	14	10	15

Times Each Choice Profile Was Included in a Survey

Profile Number	Number Sent
15	134
10	136
14	138
29	138
26	139
2	140
18	140
11	141
19	141
16	142
32	142
9	143
30	143
12	144
17	144
28	144
22	145
6	146
7	146
1	147
13	147
20	147
23	147
27	147
5	148
8	148
21	148
24	149
25	149
3	150
31	151
4	152

APPENDIX 4 – SCENARIOS FOR VEHICLE CHOICE PREDICTIONS

Scenario Attributes for Figure 4.44

	Gasoline	Alternative Fuel	Hybrid-Electric	Hydrogen Fuel-Cell
Capital Cost	20000	25000	30000	60000
Fuel Cost	200	200	150	250
Fual Availability	1	0.1	1	0.1
Express Access	1	1	1	1
Power	0	1	1	1

Scenario Attributes for Figure 4.45

	Gasoline	Alternative Fuel	Hybrid-Electric	Hydrogen Fuel-Cell
Capital Cost	25000	28000	32000	30000
Fuel Cost	225	225	175	200
Fual Availability	1	0.1	1	0.5
Express Access	1	1	1	0
Power	0	1	1	0

Scenario Attributes for Figure 4.46

	Gasoline	Alternative Fuel	Hybrid-Electric	Hydrogen Fuel-Cell
Capital Cost	25000	22000	32000	60000
fFuel Cost	225	175	175	250
Fual Availability	1	0.5	1	0.1
Express Access	1	0	1	1
Power	0	0	1	1

Scenario Attributes for Figure 4.47

	Gasoline	Alternative Fuel	Hybrid-Electric	Hydrogen Fuel-Cell
Capital Cost	25000	24000	28000	50000
Fuel Cost	225	185	130	225
Fual Availability	1	0.25	1	0.25
Express Access	1	0	0	0
Power	0	0	0	0

Scenario Attributes for Figure 5.5

	Gas - High	Gas - Low	Propane	Nat Gas	Diesel	Meth	Ethanol	Electric	Hybrid	Fuel Cell
CC	19000	21000	25000	25000	25000	25000	25000	40000	35000	60000
OC	1500	2000	1500	1500	1500	1500	1500	1500	1500	1000
FA	1	1	0.1	0.1	0.1	0.1	0.1	1	1	0.1
Exp	1	1	1	1	1	1	1	0	1	1
Pow	0	0	0	0	0	0	0	1	1	1

Scenario Attributes for Figure 5.6

	Gas - High	Gas - Low	Propane	Nat Gas	Diesel	Meth	Ethanol	Electric	Hybrid	Fuel Cell
CC	20000	25000	20000	20000	20000	25000	25000	40000	35000	60000
OC	1500	2000	1250	1250	1250	1500	1500	1500	1500	1000
FA	1	1	0.5	0.5	0.5	0.1	0.1	1	1	0.1
Exp	1	1	0	0	0	1	1	0	1	1
Pow	1	0	0	0	0	0	0	1	1	1

Scenario Attributes for Figure 5.7

	Gas - High	Gas - Low	Propane	Nat Gas	Diesel	Meth	Ethanol	Electric	Hybrid	Fuel Cell
CC	20000	25000	25000	25000	25000	25000	25000	25000	25000	35000
OC	1500	2000	1500	1500	1500	1500	1500	1250	1250	1000
FA	1	1	0.1	0.1	0.1	0.1	0.1	1	1	0.5
Exp	1	1	1	1	1	1	1	0	1	1
Pow	1	0	0	0	0	0	0	1	0	0

Scenario Attributes for Figure 5.8

	Gas - High	Gas - Low	Propane	Nat Gas	Diesel	Meth	Ethanol	Electric	Hybrid	Fuel Cell
CC	20000	25000	25000	25000	25000	20000	20000	40000	35000	60000
OC	1500	2000	1500	1500	1500	1250	1250	1500	1500	1000
FA	1	1	0.1	0.1	0.1	0.75	0.75	1	1	0.1
Exp	1	1	1	1	1	0	0	0	1	1
Pow	1	0	0	0	0	0	0	1	1	1

APPENDIX 5 – SCENARIOS FOR MODE CHOICE PREDICTIONS

Scenario Attributes for Figure 4.15

	SOV	HOV	Trans	Park	W/C
Cost ($/month)	150	120	100	150	0
Driving Time	22	20	38	40	65
Pickup/Dropoff Time	0	10	0	0	0
Walking/Waiting Time	0	0	15	10	0
Transfers	0	0	0.5	0	0
Cycling Path	0	0	0	0	0

Scenario Attributes for Figure 4.16

	SOV	HOV	Trans	Park	W/C
Cost ($/month)	150	100	100	150	0
Driving Time	30	30	30	30	90
Pickup/Dropoff Time	0	5	0	0	0
Walking/Waiting Time	0	0	5	5	0
Transfers	0	0	0	0	0
Cycling Path	0	0	0	0	0.5

Scenario Attributes for Figure 4.48

	SOV	HOV	Transit	W/C
Cost ($/month)	150	120	100	0
Driving Time	22	20	38	65
Pickup/Dropoff Time	0	10	0	0
Walking/Waiting Time	0	0	15	0
Transfers	0	0	0.5	0
Cycling Path	0	0	0	0

Scenario Attributes for Figure 4.49

	SOV	HOV	Transit	W/C
Cost ($/month)	150	75	100	0
Driving Time	22	15	38	65
Pickup/Dropoff Time	0	5	0	0
Walking/Waiting Time	0	0	15	0
Transfers	0	0	0.5	0
Cycling Path	0	0	0	0

Scenario Attributes for Figure 4.50

	SOV	HOV	Transit	W/C
Cost ($/month)	150	120	60	0
Driving Time	22	20	25	65
Pickup/Dropoff Time	0	10	0	0
Walking/Waiting Time	0	0	5	0
Transfers	0	0	0	0

Cycling Path	0	0	0	0

Scenario Attributes for Figure 4.51

	SOV	HOV	Transit	W/C
Cost ($/month)	150	120	100	0
Driving Time	22	20	38	45
Pickup/Dropoff Time	0	10	0	0
Walking/Waiting Time	0	0	15	0
Transfers	0	0	0.5	0
Cycling Path	0	0	0	1

Scenario Attributes for Figure 5.9

	SOV	HOV	Transit	W/C
Cost ($/year)	2000	1500	1000	0
Driving Time	22	20	38	65
Pickup/Dropoff Time	0	0	15	0
Walking/Waiting Time	0	10	0	0
Transfers	0	0	0.5	0
Cycling Path	0	0	0	0

Scenario Attributes for Figure 5.10

	SOV	HOV	Transit	W/C
Cost ($/year)	2000	1000	1000	0
Driving Time	25	17	38	65
Pickup/Dropoff Time	0	0	15	0
Walking/Waiting Time	0	5	0	0
Transfers	0	0	0.5	0
Cycling Path	0	0	0	0

Scenario Attributes for Figure 5.11

	SOV	HOV	Transit	W/C
Cost ($/year)	2000	1500	500	0
Driving Time	25	20	20	65
Pickup/Dropoff Time	0	0	10	0
Walking/Waiting Time	0	10	0	0
Transfers	0	0	0.1	0
Cycling Path	0	0	0	0

Scenario Attributes for Figure 5.12

	SOV	HOV	Transit	W/C
Cost ($/year)	2000	1500	1000	0
Driving Time	25	20	38	40
Pickup/Dropoff Time	0	0	15	0
Walking/Waiting Time	0	10	0	0
Transfers	0	0	0	0
Cycling Path	0	0	0	1

APPENDIX 6 – VEHICLE CHOICE SUB-MODELS

	All Obs.	
	Beta Coeff.	b/St. Err.
Capital Cost	-9.01E-05	-5.76
Fuel Cost	-4.60E-03	-3.38
Fuel	1.16	8.47
Express	-0.16	-3.09
Power	-0.22	-4.47
ASC -	-1.70	-
ASC - AFV	-2.01	-
ASC - HEV	-0.36	-4.18
Log-	-3625.61	
Observations	3278	
Discount	24%	

Gray cells in the beta coefficient column are the expected sign.

Gray cells in the beta/St. Error column are statistically significant.

	Region									
	Atlantic		Quebec		Ontario		Praries		BC	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Capital Cost	-1.06E-04	-1.83	-9.60E-05	-3.05	-7.70E-05	-3.07	-1.68E-04	-4.45	-2.59E-06	-0.05
Fuel Cost	9.51E-03	1.99	-8.80E-03	-2.67	-1.44E-02	-6.06	1.55E-03	0.96	3.47E-03	0.71
Fuel Availability	0.66	1.37	1.36	4.62	1.18	5.34	1.34	3.99	0.95	2.55
Express Access	0.08	0.47	-0.21	-1.90	-0.18	-2.13	-0.17	-1.34	-0.13	-0.88
Power	-0.38	-2.22	-0.17	-1.62	-0.15	-1.82	-0.30	-2.46	-0.32	-2.40
ASC - Gasoline	-1.53	-4.44	-1.35	-6.69	-1.78	-10.96	-1.93	-8.09	-2.01	-7.10
ASC - AFV	-2.00	-6.59	-1.79	-10.06	-1.96	-14.12	-2.55	-10.64	-1.84	-8.04
ASC - HEV	0.53	1.76	-0.40	-2.09	-0.79	-5.45	-0.31	-1.59	-0.10	-0.39
Log-likelihood	-310.46		-867.04		-1334.85		-622.54		-446.51	
Observations	286		772		1226		583		411	
Discount Rates	-13%		13%		6%		-130%		-1%	

	City Size					
	Large		Medium		Small	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Capital Cost	-6.76E-05	-3.14	-1.35E-04	-4.56	-1.07E-04	-2.87
Fuel Cost	-1.05E-02	-4.80	-1.59E-02	-4.77	2.74E-03	1.83
Fuel Availability	1.10	5.77	1.28	4.91	1.24	3.97
Express Access	-0.23	-3.11	-0.15	-1.57	0.01	0.09
Power	-0.20	-2.89	-0.14	-1.53	-0.39	-3.54
ASC - Gasoline	-1.51	-11.07	-1.97	-10.37	-1.77	-7.93
ASC - AFV	-1.81	-15.57	-2.41	-13.10	-1.91	-10.00
ASC - HEV	-0.50	-4.03	-0.90	-5.07	0.07	0.37
Log-likelihood	-1875.30		-973.39		-742.45	
Observations	1670		924		684	
Discount Rates	8%		10%		-47%	

	Major Cities					
	Toronto		Vancouver		Montreal	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Capital Cost	-5.52E-05	-1.80	-4.02E-06	-0.07	-1.08E-04	-2.91
Fuel Cost	-1.73E-02	-4.99	1.87E-03	0.34	-7.87E-03	-2.25
Fuel Availability	1.20	4.12	0.72	1.79	1.26	3.80
Express Access	-0.26	-2.36	-0.19	-1.25	-0.21	-1.69
Power	-0.11	-1.02	-0.33	-2.24	-0.22	-1.94
ASC - Gasoline	-1.59	-7.52	-2.07	-6.55	-1.20	-5.33
ASC - AFV	-1.84	-10.27	-1.93	-7.62	-1.68	-8.69
ASC - HEV	-0.84	-4.35	-0.05	-0.18	-0.33	-1.57
Log-likelihood	-780.54		-373.59		-699.22	
Observations	709		353		608	
Discount Rates	4%		-3%		16%	

	Age							
	<25 years		26 to 40 years		41 to 55 years		>56 years	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Capital Cost	-2.65E-04	-3.60	-7.65E-05	-2.64	-8.76E-05	-3.60	-8.76E-05	-2.68
Fuel Cost	-3.36E-02	-4.53	-6.35E-04	-0.44	-5.77E-03	-2.48	-1.18E-02	-2.83
Fuel Availability	2.53	4.77	1.20	4.85	1.25	5.61	0.50	1.71
Express Access	-0.40	-2.10	-0.17	-1.86	-0.09	-1.06	-0.17	-1.46
Power	-0.66	-3.53	-0.26	-2.99	-0.17	-2.18	-0.07	-0.66
ASC - Gasoline	-2.39	-6.41	-1.81	-10.12	-1.92	-11.96	-0.85	-4.06
ASC - AFV	-1.78	-6.03	-2.12	-12.91	-2.32	-15.28	-1.43	-8.71
ASC - HEV	-1.39	-4.00	-0.14	-1.00	-0.65	-4.51	-0.19	-0.94
Log-likelihood	-282.95		-1119.60		-1339.95		-823.77	
Observations	300		1053		1226		687	
Discount Rates	9%		145%		18%		9%	

	Education							
	Grade 9 or less		Grade 12		College		University	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Capital Cost	-7.62E-05	-1.08	-1.31E-04	-3.08	-8.23E-05	-2.94	-8.61E-05	-3.79
Fuel Cost	-2.77E-02	-2.57	-9.25E-03	-2.71	-1.59E-03	-0.95	-5.56E-03	-2.47
Fuel Availability	0.41	0.65	0.65	2.04	1.59	6.37	1.20	5.78
Express Access	-0.79	-2.90	-0.13	-1.08	-0.09	-1.01	-0.17	-2.17
Power	-0.09	-0.39	-0.23	-2.06	-0.20	-2.25	-0.24	-3.17
ASC - Gasoline	0.32	0.73	-1.18	-5.11	-1.87	-10.70	-2.10	-13.60
ASC - AFV	-0.30	-0.98	-1.62	-8.66	-2.39	-13.55	-2.19	-16.05
ASC - HEV	-0.67	-1.37	-0.01	-0.04	-0.46	-3.07	-0.54	-4.04
Log-likelihood	-181.17		-705.10		-1153.40		-1492.04	
Observations	139		629		1075		1401	
Discount Rates	3%		17%		62%		19%	

	Gender			
	Male		Female	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Capital Cost	-9.29E-05	-4.12	-8.74E-05	-3.96
Fuel Cost	-1.55E-03	-1.07	-1.01E-02	-4.55
Fuel Availability	1.65	7.50	0.84	4.72
Express Access	-0.15	-1.89	-0.15	-2.16
Power	-0.27	-3.41	-0.18	-2.83
ASC - Gasoline	-1.81	-12.06	-1.65	-12.35
ASC - AFV	-2.28	-15.60	-1.82	-16.57
ASC - HEV	-0.62	-4.84	-0.28	-2.29
Log-likelihood	-1501.12		-2070.51	
Observations	1345		1909	
Discount Rates	72%		10%	

	Income									
	< $20,000		$20,001 to $40,000		$40,001 to $60,000		$60,001 to $80,000		> $80,000	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Capital Cost	-1.62E-04	-2.12	-1.14E-04	-2.54	-1.03E-04	-2.98	-4.53E-05	-1.07	-8.67E-05	-3.63
Fuel Cost	-1.00E-02	-1.28	-1.11E-02	-2.52	-1.44E-02	-3.80	-1.39E-02	-3.88	9.49E-04	0.69
Fuel Availability	1.43	2.82	1.47	4.52	0.85	2.82	0.55	1.68	1.45	5.88
Express Access	0.15	0.76	-0.16	-1.37	-0.21	-1.90	-0.01	-0.08	-0.21	-2.29
Power	-0.54	-2.96	-0.03	-0.28	-0.22	-2.05	-0.04	-0.35	-0.39	-4.33
ASC - Gasoline	-1.47	-4.31	-1.62	-7.02	-1.55	-7.11	-1.40	-5.66	-2.12	-11.86
ASC - AFV	-1.41	-5.18	-1.83	-9.36	-2.28	-10.58	-1.47	-7.74	-2.47	-14.38
ASC - HEV	-0.61	-1.65	-0.59	-2.62	-0.39	-1.96	-0.22	-1.01	-0.51	-3.56
Log-likelihood	-299.92		-680.35		-745.03		-598.10		-1116.88	
Observations	248		614		714		540		1044	
Discount Rates	19%		12%		9%		4%		-110%	

	Car Access	
	Beta Coeff.	b/St. Err.
Capital Cost	-9.18E-05	-5.68
Fuel Cost	-4.22E-03	-3.02
Fuel Availability	1.12	7.75
Express Access	-0.15	-2.79
Power	-0.23	-4.39
ASC - Gasoline	-1.68	-16.24
ASC - AFV	-2.04	-22.09
ASC - HEV	-0.31	-3.45
Log-likelihood	-3306.36	
Observations	3001	
Discount Rates	26%	

	Vehicle Class							
	Small Cars		Medium Cars		Large Cars (includes minivans)		Trucks/SUV's	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Capital Cost	-1.68E-04	-4.27	-8.06E-05	-2.63	-5.89E-05	-2.06	-1.04E-04	-3.07
Fuel Cost	-1.33E-02	-3.88	-7.82E-03	-2.68	-1.18E-02	-3.68	1.40E-03	0.93
Fuel Availability	1.67	6.19	1.13	4.35	0.78	2.76	1.01	2.59
Express Access	-0.21	-2.06	-0.21	-2.16	-0.03	-0.24	-0.08	-0.53
Power	-0.24	-2.54	-0.26	-2.88	-0.21	-2.00	-0.18	-1.29
ASC - Gasoline	-1.95	-10.12	-1.65	-8.79	-1.55	-7.59	-1.40	-5.20
ASC - AFV	-2.06	-12.23	-1.84	-11.52	-2.00	-10.88	-2.15	-8.57
ASC - HEV	-0.80	-4.58	-0.31	-1.81	-0.44	-2.35	-0.21	-0.92
Log-likelihood	-978.58		-1015.88		-829.80		-475.32	
Observations	914		931		751		411	
Discount Rates	15%		12%		6%		-89%	

APPENDIX 7 – MODE CHOICE SUB-MODELS

	All Obs	
	Beta Coeff.	b/St. Err.
Cost	-2.84E-03	-5.29
Driving Time	-4.42E-02	-13.85
P/D Time	-7.94E-02	-5.07
W/W Time	-7.32E-02	-8.36
Transfers	-0.15896	-2.00
Cycling Path	0.17328	1.26
Asc - SOV	-0.53256	-3.94
Asc - HOV	-0.47297	-2.73
Asc - Transit	-0.46235	-3.02
Asc - P & R	-1.94689	-10.80
Log-likelihood	-4088.34	
Observations	3335	

Gray cells in the beta coefficient column are the expected sign.

Gray cells in the beta/St. Error column are statistically significant.

	Region									
	Atlantic		Quebec		Ontario		Praries		BC	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Cost	-6.39E-03	-2.82	-3.94E-03	-3.21	-4.55E-03	-5.51	-2.29E-04	-0.40	-7.55E-03	-3.37
Driving Time	-4.78E-02	-3.92	-5.02E-02	-6.28	-3.75E-02	-8.05	-5.66E-02	-6.28	-5.21E-02	-6.21
P/D Time	-1.03E-01	-1.86	-1.01E-01	-3.14	-8.47E-02	-3.30	-4.87E-02	-1.31	-5.95E-02	-1.36
W/W Time	-8.06E-02	-2.83	-6.89E-02	-3.85	-9.95E-02	-6.69	-4.42E-02	-2.11	-5.70E-02	-2.30
Transfers	-0.21387	-0.80	0.140398	0.85	-0.28503	-2.18	-0.1727	-0.89	-0.37702	-1.66
Cycling Path	-0.22734	-0.47	0.060709	0.18	0.154604	0.71	0.587428	1.74	0.256824	0.71
Asc - SOV	-0.41663	-0.77	0.027963	0.09	-0.24692	-1.18	-0.65793	-2.17	-1.1464	-2.92
Asc - HOV	-0.39389	-0.60	0.271117	0.71	-0.32362	-1.17	-0.80507	-1.95	-1.17518	-2.45
Asc - Transit	-0.15876	-0.28	-0.04875	-0.14	-0.12484	-0.52	-0.85469	-2.32	-1.0412	-2.39
Asc - P & R	-2.17904	-2.99	-1.82867	-4.35	-1.3228	-4.76	-2.34294	-5.59	-2.29952	-4.45
Log-likelihood	-339.407		-909.788		-1555.63		-723.699		-505.708	
Observations	282		758		1277		597		421	

	City Size					
	Large		Medium		Small	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Cost	-4.76E-03	-5.61	-7.00E-03	-5.24	-5.33E-04	-0.99
Driving Time	-4.79E-02	-9.98	-4.72E-02	-7.58	-3.75E-02	-6.07
P/D Time	-7.61E-02	-3.52	-8.08E-02	-2.72	-9.08E-02	-2.59
W/W Time	-8.76E-02	-7.06	-4.92E-02	-3.06	-8.03E-02	-3.99
Transfers	-0.23605	-2.12	-0.09944	-0.67	-0.14988	-0.84
Cycling Path	0.147494	0.73	0.153142	0.61	0.225184	0.78
Asc - SOV	-0.31902	-1.62	-0.08605	-0.33	-0.85903	-3.09
Asc - HOV	-0.34991	-1.42	-0.22768	-0.70	-0.67018	-1.76
Asc - Transit	-0.14896	-0.68	-0.37665	-1.30	-0.783	-2.34
Asc - P & R	-1.65493	-6.35	-1.77536	-5.02	-2.04972	-5.49
Log-likelihood	-2070.64		-1151.18		-842.321	
Observations	1707		944		684	

	Major Cities					
	Toronto		Vancouver		Montreal	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Cost	-5.66E-03	-4.58	-6.42E-03	-2.74	-4.18E-03	-3.16
Driving Time	-4.36E-02	-6.05	-5.21E-02	-5.63	-5.72E-02	-5.75
P/D Time	-7.39E-02	-2.22	-7.21E-02	-1.50	-8.38E-02	-2.35
W/W Time	-1.22E-01	-6.09	-5.84E-02	-2.26	-6.95E-02	-3.39
Transfers	-0.51016	-2.94	-0.39817	-1.64	0.168567	0.90
Cycling Path	0.065607	0.22	0.24327	0.62	0.198133	0.47
Asc - SOV	-0.05389	-0.19	-1.08238	-2.58	0.070457	0.19
Asc - HOV	-0.29398	-0.79	-1.06871	-2.05	0.207944	0.46
Asc - Transit	0.306581	0.93	-0.83024	-1.79	-0.05376	-0.13
Asc - P & R	-0.97552	-2.54	-2.56592	-4.46	-1.70727	-3.55
Log-likelihood	-900.383		-435.735		-709.061	
Observations	750		361		596	

	Age							
	<25 years		26 to 40 years		41 to 55 years		>56 years	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Cost	-1.17E-02	-3.44	-9.78E-04	-1.78	-3.23E-03	-3.75	-1.36E-02	-6.68
Driving Time	-7.04E-02	-5.94	-3.11E-02	-6.99	-5.59E-02	-9.39	-3.67E-02	-3.50
P/D Time	-1.39E-01	-2.68	-7.90E-02	-2.96	-7.85E-02	-2.89	-5.55E-02	-1.64
W/W Time	-3.89E-02	-1.23	-7.47E-02	-4.69	-8.07E-02	-5.18	-8.01E-02	-4.75
Transfers	-0.4595	-1.54	-0.32847	-2.24	-0.04298	-0.31	-0.05029	-0.33
Cycling Path	0.096492	0.22	0.219435	0.97	0.12019	0.54	0.637172	1.36
Asc - SOV	-1.18392	-2.05	-0.62369	-2.94	-0.31959	-1.48	1.381179	2.85
Asc - HOV	-0.4767	-0.79	-0.28177	-0.97	-0.70058	-2.41	0.99814	1.90
Asc - Transit	-1.40551	-2.48	-0.40028	-1.56	-0.64244	-2.53	1.599062	3.32
Asc - P & R	-2.74726	-3.78	-2.1475	-6.87	-1.87363	-6.28	0.438941	0.82
Log-likelihood	-322.914		-1318.18		-1466.16		-865.071	
Observations	300		1074		1254		701	

	Education							
	Grade 9 or less		Grade 12		College		University	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Cost	-5.15E-03	-0.97	-5.60E-03	-4.24	-6.52E-04	-1.24	-5.68E-03	-5.89
Driving Time	2.26E-02	1.20	-5.81E-02	-6.86	-3.08E-02	-6.45	-5.70E-02	-10.67
P/D Time	-2.51E-02	-0.29	-3.92E-02	-1.13	-1.19E-01	-4.37	-7.45E-02	-3.09
W/W Time	-3.25E-02	-0.83	-5.79E-02	-2.85	-7.06E-02	-4.57	-9.14E-02	-6.73
Transfers	0.326596	0.88	-0.12935	-0.71	-0.1815	-1.28	-0.22756	-1.88
Cycling Path	-1.01612	-1.18	-0.13388	-0.42	0.229239	0.91	0.271717	1.34
Asc - SOV	1.033809	1.16	-0.71202	-2.29	-0.33321	-1.45	-0.51444	-2.44
Asc - HOV	0.18689	0.19	-0.98912	-2.47	0.123985	0.41	-0.61792	-2.32
Asc - Transit	0.392203	0.47	-0.97135	-2.70	-0.28129	-1.03	-0.2668	-1.15
Asc - P & R	-1.09541	-1.06	-2.02923	-4.93	-1.90395	-6.08	-1.71703	-6.11
Log-likelihood	-162.391		-790.401		-1334.78		-1732.34	
Observations	134		649		1094		1432	

	Gender			
	Male		Female	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Cost	-1.02E-03	-2.04	-7.20E-03	-7.45
Driving Time	-4.48E-02	-9.10	-4.83E-02	-10.72
P/D Time	-8.12E-02	-3.04	-7.50E-02	-3.82
W/W Time	-5.83E-02	-4.46	-8.69E-02	-7.29
Transfers	-0.09751	-0.81	-0.21823	-2.05
Cycling Path	0.450465	2.25	-0.02755	-0.14
Asc - SOV	-0.62073	-3.26	-0.15692	-0.80
Asc - HOV	-0.8103	-2.93	-0.12384	-0.54
Asc - Transit	-0.60336	-2.67	-0.14357	-0.67
Asc - P & R	-2.21829	-8.35	-1.41615	-5.63
Log-likelihood	-1671.28		-2345.6	
Observations	1366		1951	

	Income									
	< $20,000		$20,001 to $40,000		$40,001 to $60,000		$60,001 to $80,000		> $80,000	
	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.	Beta Coeff.	b/St. Err.
Cost	-1.78E-02	-4.20	-1.19E-02	-5.69	-4.52E-03	-3.27	-6.35E-03	-5.12	-6.64E-04	-1.35
Driving Time	-2.25E-02	-2.45	-4.12E-02	-5.86	-4.31E-02	-6.66	-5.13E-02	-5.63	-6.24E-02	-8.94
P/D Time	-9.63E-02	-1.52	-6.66E-02	-1.95	-7.80E-02	-2.31	-7.14E-02	-1.96	-8.03E-02	-2.65
W/W Time	-3.67E-02	-1.21	-5.14E-02	-2.65	-5.93E-02	-3.49	-1.19E-01	-4.73	-1.23E-01	-6.70
Transfers	-0.47023	-1.67	0.130239	0.71	-0.17414	-1.12	-0.53435	-2.52	-0.17631	-1.15
Cycling Path	-0.03495	-0.08	-0.12145	-0.39	0.394946	1.33	0.301214	0.77	0.144311	0.57
Asc - SOV	1.889143	3.00	-0.2666	-0.74	-0.25403	-0.87	-0.18804	-0.48	-0.98552	-4.08
Asc - HOV	1.069942	1.64	-0.0149	-0.04	-0.16109	-0.43	-0.05714	-0.12	-1.3902	-4.14
Asc - Transit	1.13658	1.92	-0.36263	-0.97	0.014994	0.05	0.135366	0.31	-0.85615	-2.97
Asc - P & R	0.347467	0.47	-1.98427	-4.16	-1.28891	-3.50	-1.03334	-2.06	-2.387	-7.17
Log-likelihood	-308.621		-737.66		-921.01		-642.087		-1194.53	
Observations	253		626		727		547		1058	

	Commuter	
	Beta Coeff.	b/St. Err.
Cost	-2.16E-03	-4.21
Driving Time	-4.27E-02	-13.10
P/D Time	-9.61E-02	-5.34
W/W Time	-7.76E-02	-7.36
Transfers	-0.15028	-1.56
Cycling Path	0.162641	1.14
Asc - SOV	-0.5302	-3.82
Asc - HOV	-0.46731	-2.48
Asc - Transit	-0.63711	-3.81
Asc - P & R	-2.29062	-11.07
Log-likelihood	-3146.94	
Observations	2637	

APPENDIX 8 – AVAILABILITY MODIFIERS

	Case 1		Case 2		Case 3	
Vehicle Type	**Market Share**	**Availability Modifier**	**Market Share**	**Availability Modifier**	**Market Share**	**Availability Modifier**
Methanol	0%	-1.44	5%	0.21	1%	-1.33
Ethanol	1%	0.94	5%	0.14	1%	-1.40
Electric	0%	-2.67	5%	-0.44	1%	-1.99
Hybrid	1%	-5.36	5%	-2.11	4%	-2.26
Fuel-cell	0%	0.00	5%	0.01	70%	11.25
Propane	0%	-0.48	5%	0.78	1%	-0.76
Diesel	4%	1.94	5%	-0.01	1%	-1.54
Natural Gas	1%	1.31	5%	0.87	1%	-0.67
Gas – High	49%	3.10	30%	0.35	10%	-0.59
Gas – Low	44%	2.26	30%	-0.20	10%	-1.14

	Case 4		Case 5		Case 6	
Vehicle Type	**Market Share**	**Availability Modifier**	**Market Share**	**Availability Modifier**	**Market Share**	**Availability Modifier**
Methanol	2%	-0.93	4%	-0.73	10%	-0.30
Ethanol	2%	-1.00	4%	-0.80	10%	-0.37
Electric	2%	-1.58	4%	-1.39	10%	-0.96
Hybrid	2%	-3.36	4%	-3.05	10%	-2.62
Fuel-cell	2%	7.32	4%	7.59	10%	8.02
Propane	2%	-0.35	4%	-0.16	10%	0.27
Diesel	4%	-0.64	4%	-0.96	10%	-0.53
Natural Gas	2%	-0.26	4%	-0.07	10%	0.36
Gas – High	41%	0.47	34%	-0.15	10%	-1.87
Gas – Low	41%	-0.09	34%	-0.70	10%	-2.42

	Case 7		Case 8		Case 9	
Vehicle Type	**Market Share**	**Availability Modifier**	**Market Share**	**Availability Modifier**	**Market Share**	**Availability Modifier**
Methanol	0%	-3.94	7%	-0.54	5%	0.04
Ethanol	20%	3.55	7%	-0.61	10%	0.61
Electric	5%	1.58	7%	-1.19	5%	-0.61
Hybrid	50%	2.22	7%	-2.86	20%	-0.97
Fuel-cell	0%	4.39	7%	7.79	5%	0.00
Propane	0%	-3.36	7%	0.04	5%	0.62
Diesel	10%	2.70	7%	-0.76	10%	0.46
Natural Gas	0%	-3.28	7%	0.12	5%	0.70
Gas – High	15%	1.77	22%	-0.95	20%	-0.21
Gas – Low	0%	-6.05	22%	-1.50	15%	-1.04

APPENDIX 9 – INTANGIBLE COST PARAMETERS USED IN SIMULATIONS

The following tables list the actual values used in CIMS simulations. These differ from the base values described in section 5 because some of the vehicle type modifier was applied to the capital cost. The capital cost modifiers are shown immediately below.

Vehicle Type	CC Modifier
Methanol	$0
Ethanol	$0
Electric	$0
Hybrid-Electric	-$4,255
Fuel Cell	$0
Propane	$0
Diesel	-$4,255
Natural Gas	$0
Gas – High Efficiency	-$12,766
Gas – Low Efficiency	-$24,255

Business As Usual – Run 1

Mode	i
SOV	6352
HOV	8148
Transit	14345
Walk / Cycle	11947

Vehicle Type	i
Methanol	4771
Ethanol	4013
Electric	-1051
Hybrid-Electric	-521
Fuel Cell	270
Propane	4771
Diesel	4335
Natural Gas	4771
Gas – High Efficiency	6774
Gas – Low Efficiency	5067

Business As Usual – Run 2

Mode	i
SOV	6352
HOV	8148
Transit	14345
Walk / Cycle	11947

Vehicle Type	i
Methanol	8527
Ethanol	1561
Electric	5913
Hybrid-Electric	13460
Fuel Cell	270
Propane	6023
Diesel	-725

Natural Gas	1354
Gas – High Efficiency	-1312
Gas – Low Efficiency	-828

Business As Usual – Run 3

Mode	i
SOV	6352
HOV	8148
Transit	14345
Walk / Cycle	11947

Vehicle Type	i
Methanol	4301
Ethanol	3908
Electric	-1051
Hybrid-Electric	-755
Fuel Cell	270
Propane	4275
Diesel	3918
Natural Gas	4354
Gas – High Efficiency	6487
Gas – Low Efficiency	4232

Business As Usual – Run 4

Mode	i
SOV	6352
HOV	8148
Transit	14345
Walk / Cycle	11947

Vehicle Type	i
Methanol	8057
Ethanol	1457
Electric	5913
Hybrid-Electric	13225
Fuel Cell	270
Propane	5527
Diesel	-1142
Natural Gas	937
Gas – High Efficiency	-1598
Gas – Low Efficiency	-1662

$50/tonne Carbon Tax – Run 1

Mode	i
SOV	6352
HOV	8148
Transit	14345
Walk / Cycle	11947

Vehicle Type	i
Methanol	4771
Ethanol	4013
Electric	-1051
Hybrid-Electric	-521
Fuel Cell	270
Propane	4771
Diesel	4335
Natural Gas	4771
Gas – High Efficiency	6774
Gas – Low Efficiency	5067

$50/tonne Carbon Tax – Run 2

Mode	i
SOV	6352
HOV	8148
Transit	14345
Walk / Cycle	11947

Vehicle Type	i
Methanol	8527
Ethanol	1561
Electric	5913
Hybrid-Electric	13460
Fuel Cell	270
Propane	6023
Diesel	-725
Natural Gas	1354
Gas – High Efficiency	-1312
Gas – Low Efficiency	-828

$50/tonne Carbon Tax – Run 3

Mode	i
SOV	6352
HOV	8148
Transit	14345
Walk / Cycle	11947

Vehicle Type	i
Methanol	4301
Ethanol	3908
Electric	-1051
Hybrid-Electric	-755
Fuel Cell	270
Propane	4275
Diesel	3918
Natural Gas	4354
Gas – High Efficiency	6487
Gas – Low Efficiency	4232

$50/tonne Carbon Tax – Run 4

Mode	i
SOV	6352
HOV	8148
Transit	14345
Walk / Cycle	11947

Vehicle Type	i
Methanol	8057
Ethanol	1457
Electric	5913
Hybrid-Electric	13225
Fuel Cell	270
Propane	5527
Diesel	-1142
Natural Gas	937
Gas – High Efficiency	-1598
Gas – Low Efficiency	-1662

Gasoline Vehicle Disincentives – Run 1

Mode	i
SOV	6352
HOV	8148
Transit	14345
Walk / Cycle	11947

Vehicle Type	i
Methanol	4287
Ethanol	3529
Electric	-1195
Hybrid-Electric	-247
Fuel Cell	-632
Propane	4287
Diesel	3994
Natural Gas	4287
Gas – High Efficiency	7283
Gas – Low Efficiency	6189

Gasoline Vehicle Disincentives – Run 2

Mode	i
SOV	6352
HOV	8148
Transit	14345
Walk / Cycle	11947

Vehicle Type	i
Methanol	8043
Ethanol	1077
Electric	5770
Hybrid-Electric	13734
Fuel Cell	-632
Propane	5539
Diesel	-1066
Natural Gas	870
Gas – High Efficiency	-803
Gas – Low Efficiency	294

Gasoline Vehicle Disincentives – Run 3

Mode	i
SOV	6352
HOV	8148
Transit	14345
Walk / Cycle	11947

Vehicle Type	i
Methanol	3817
Ethanol	3424
Electric	-1195
Hybrid-Electric	-481
Fuel Cell	-632
Propane	3791
Diesel	3577
Natural Gas	3869
Gas – High Efficiency	6996
Gas – Low Efficiency	5354

Gasoline Vehicle Disincentives – Run 4

Mode	i
SOV	6352
HOV	8148
Transit	14345
Walk / Cycle	11947

Vehicle Type	i
Methanol	7573
Ethanol	972
Electric	5770
Hybrid-Electric	13499
Fuel Cell	-632
Propane	5043
Diesel	-1483
Natural Gas	453
Gas – High Efficiency	-1089
Gas – Low Efficiency	-540

SOV Disincentives – Run 1

Mode	i
SOV	6912
HOV	7402
Transit	9428
Walk / Cycle	9532

Vehicle Type	i
Methanol	4771
Ethanol	4013
Electric	-1051
Hybrid-Electric	-521
Fuel Cell	270
Propane	4771
Diesel	4335
Natural Gas	4771
Gas – High Efficiency	6774
Gas – Low Efficiency	5067

SOV Disincentives – Run 2

Mode	i
SOV	6912
HOV	7402
Transit	9428
Walk / Cycle	9532

Vehicle Type	i
Methanol	8527
Ethanol	1561
Electric	5913
Hybrid-Electric	13460
Fuel Cell	270
Propane	6023
Diesel	-725
Natural Gas	1354
Gas – High Efficiency	-1312
Gas – Low Efficiency	-828

SOV Disincentives – Run 3

Mode	i
SOV	6912
HOV	7402
Transit	9428
Walk / Cycle	9532

Vehicle Type	i
Methanol	4301
Ethanol	3908
Electric	-1051
Hybrid-Electric	-755
Fuel Cell	270
Propane	4275
Diesel	3918
Natural Gas	4354
Gas – High Efficiency	6487
Gas – Low Efficiency	4232

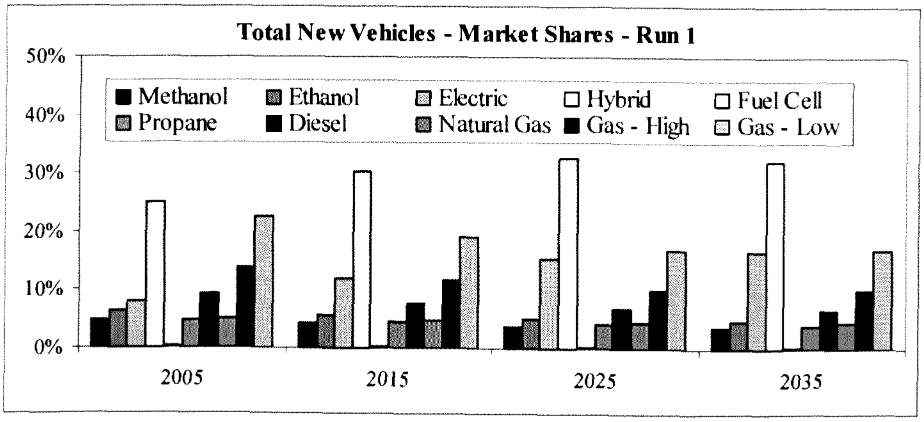
SOV Disincentives – Run 4

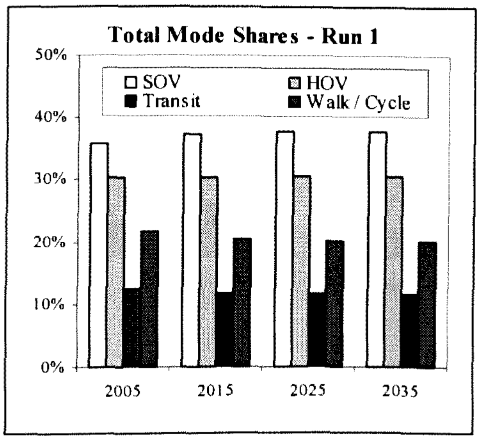
Mode	i
SOV	6912
HOV	7402
Transit	9428
Walk / Cycle	9532

Vehicle Type	i
Methanol	8057
Ethanol	1457
Electric	5913
Hybrid-Electric	13225
Fuel Cell	270
Propane	5527
Diesel	-1142
Natural Gas	937
Gas – High Efficiency	-1598
Gas – Low Efficiency	-1662

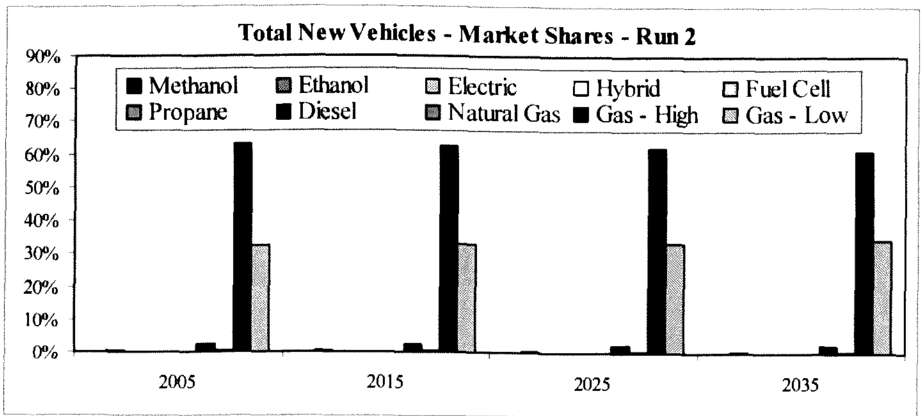
APPENDIX 10 – ADDITIONAL SIMULATION RESULTS

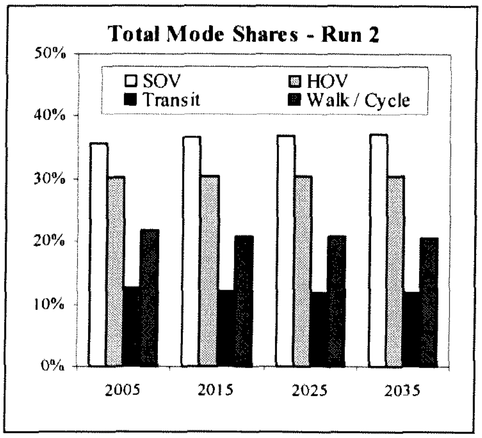
Business as Usual – Run 1



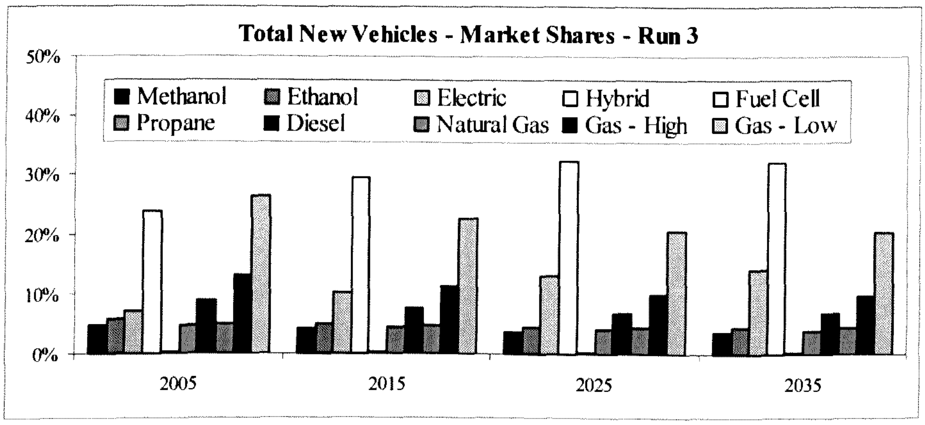


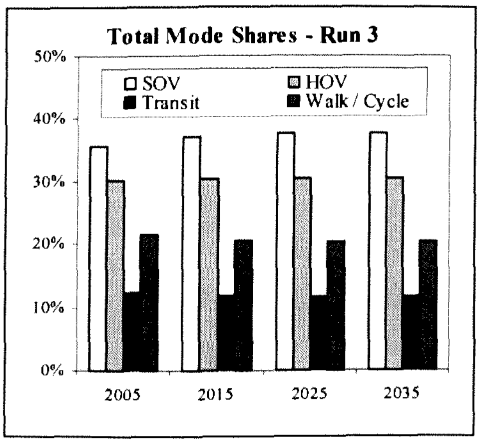
Business as Usual – Run 2



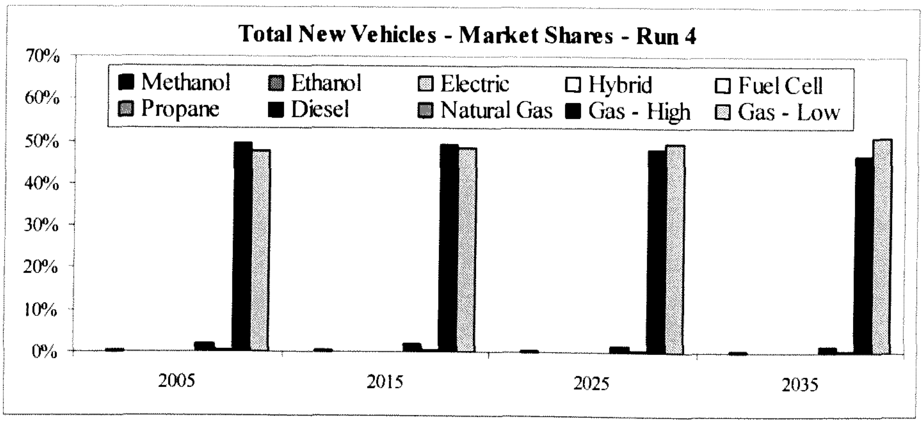


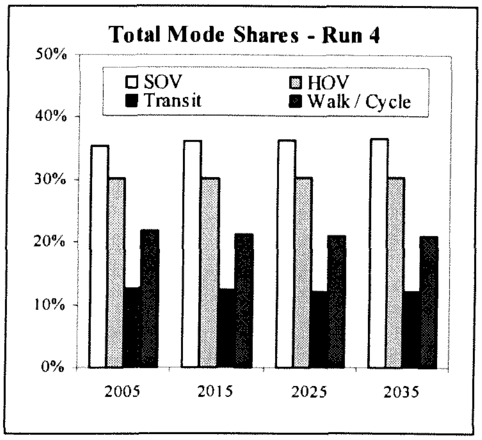
Business as Usual – Run 3



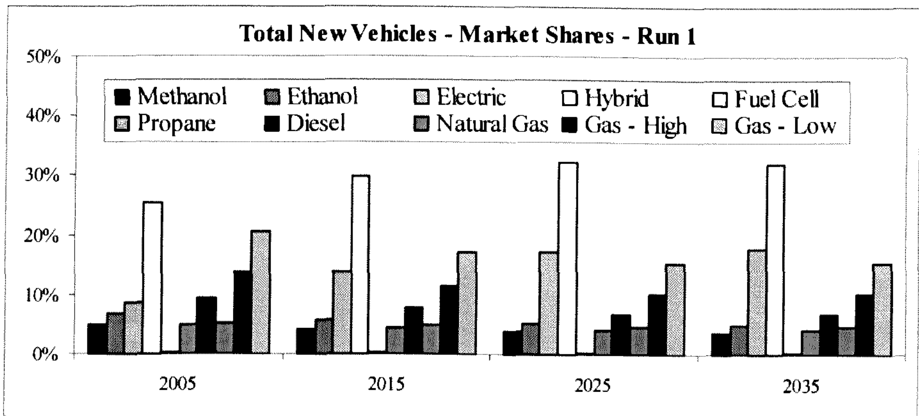


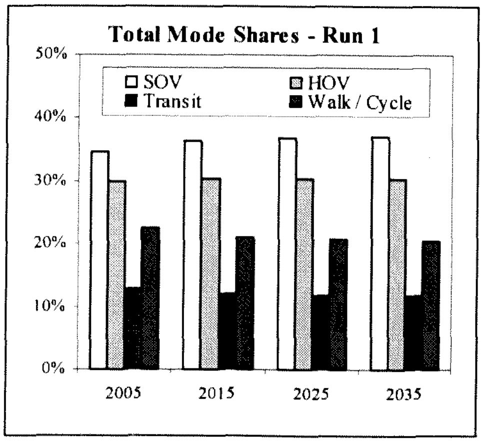
Business as Usual – Run 4





$50/tonne Carbon Tax – Run 1





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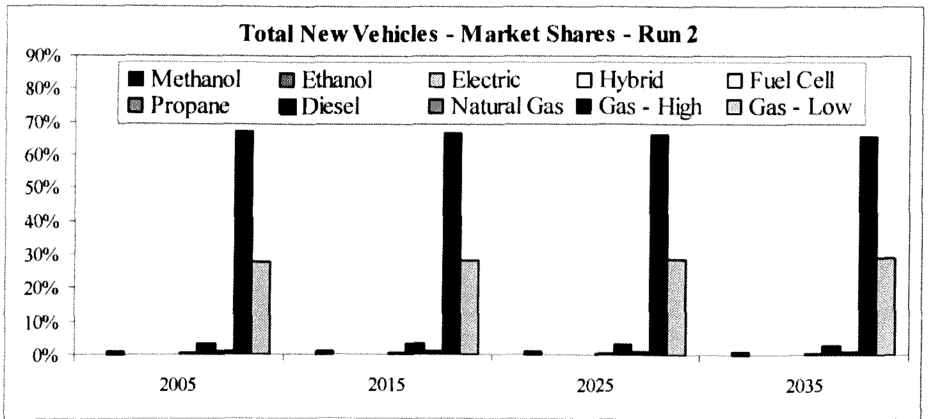

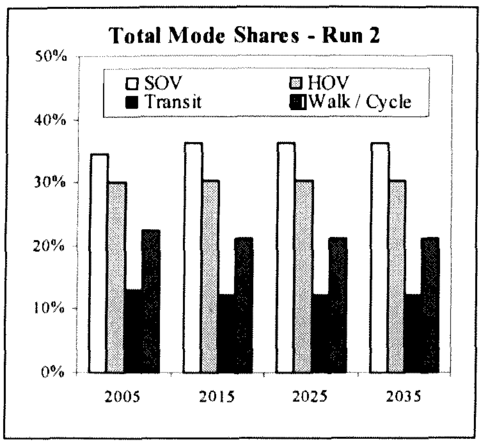

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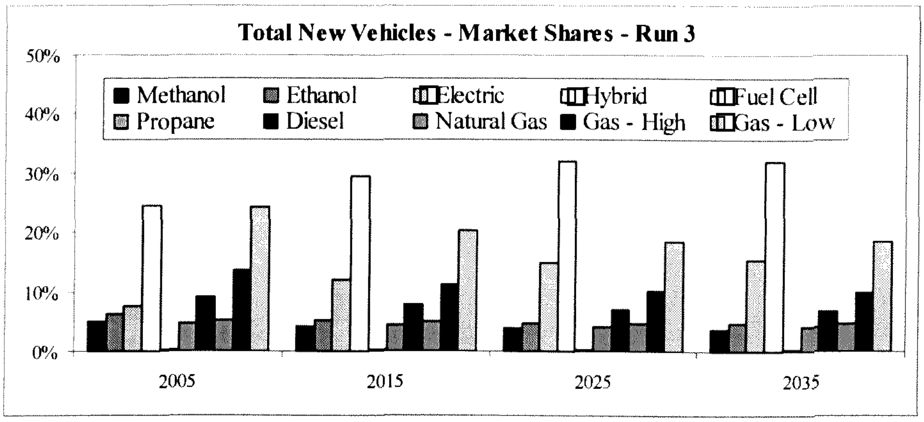
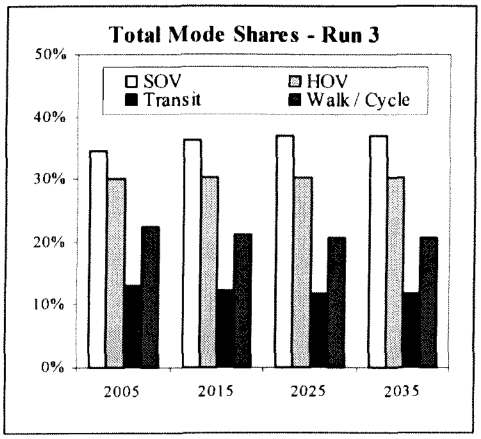
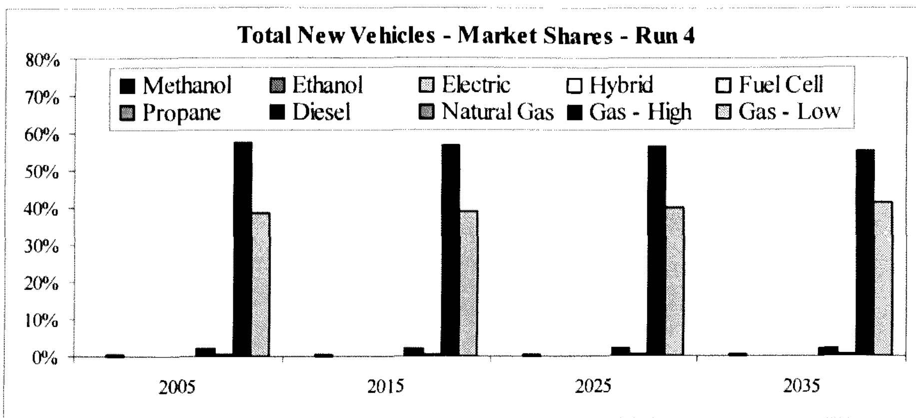
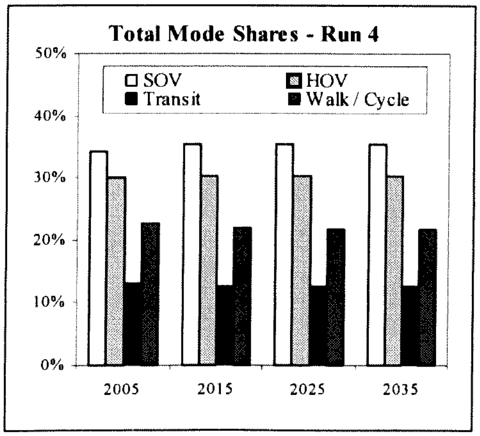


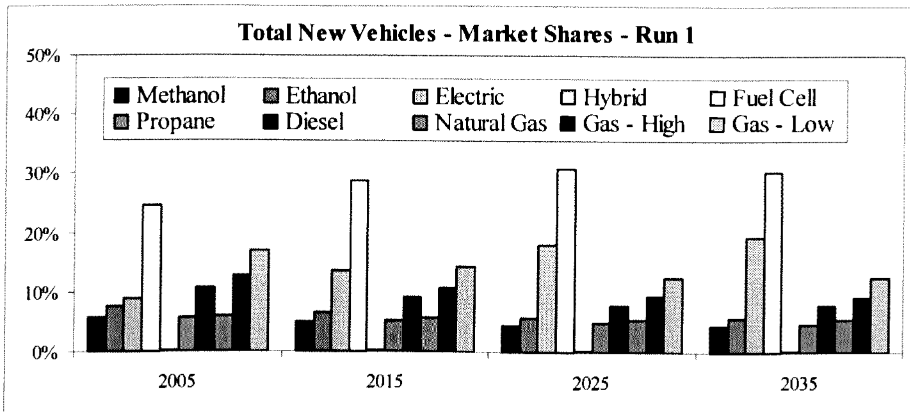


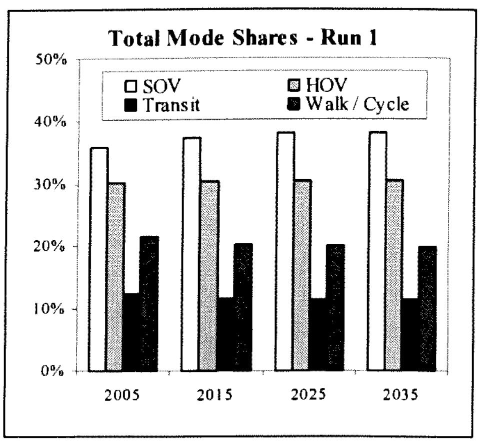
$50/tonne Carbon Tax – Run 4





Gasoline Vehicle Disincentives – Run 1





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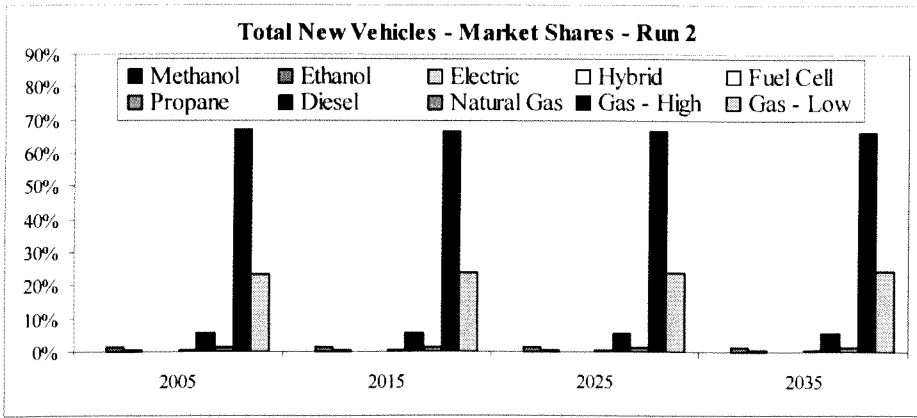
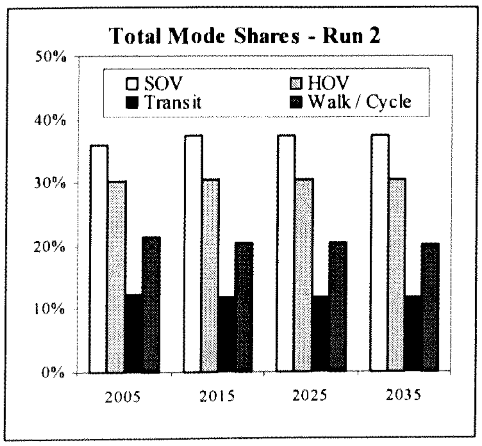
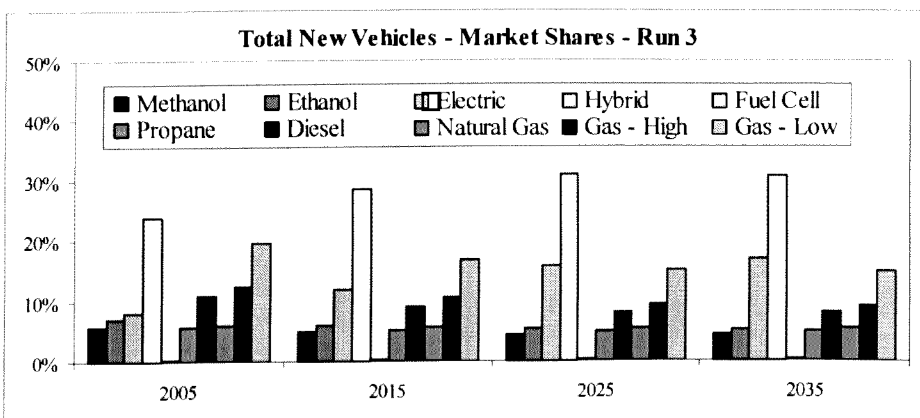
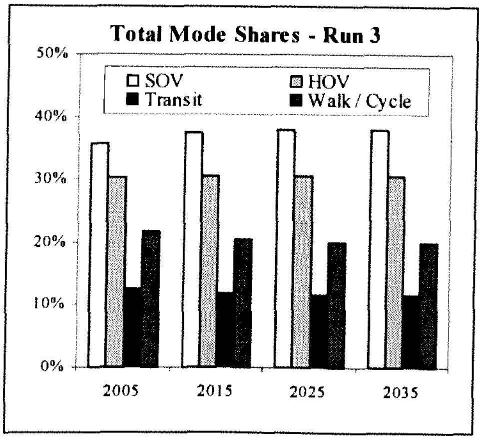


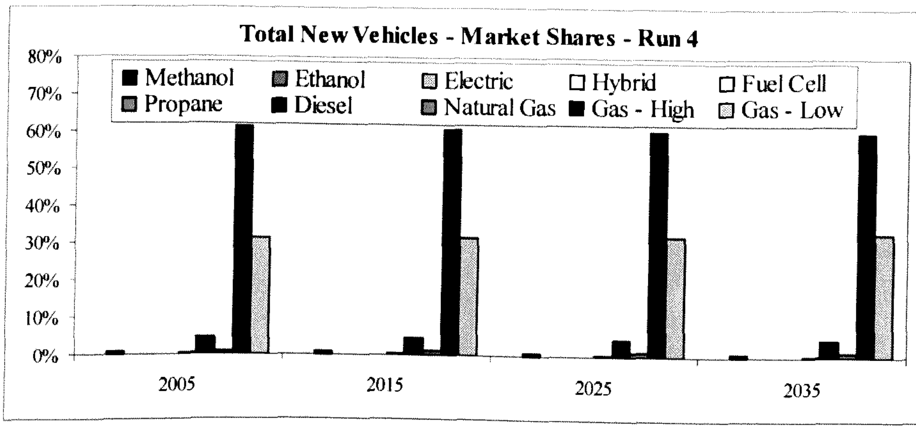


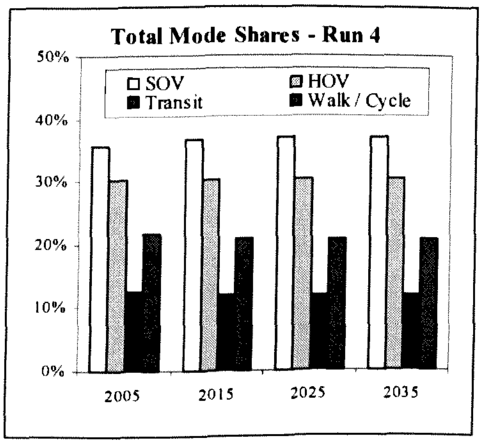
Gasoline Vehicle Disincentives – Run 3



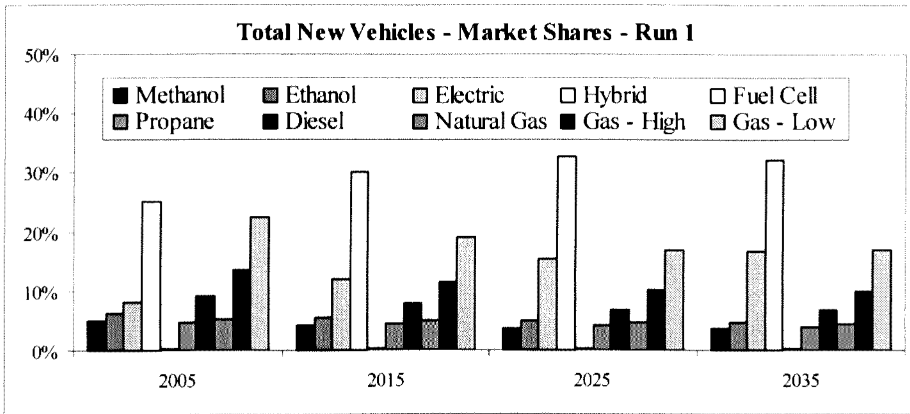


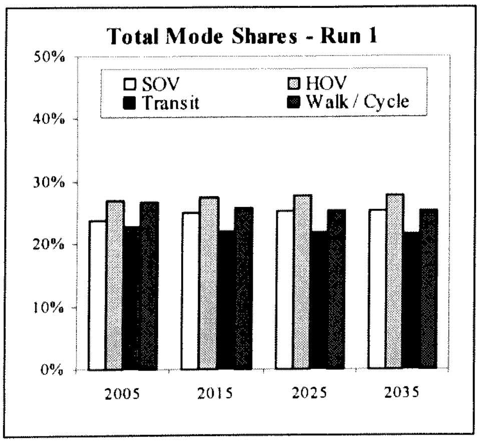
Gasoline Vehicle Disincentives – Run 4





SOV Disincentives – Run 1





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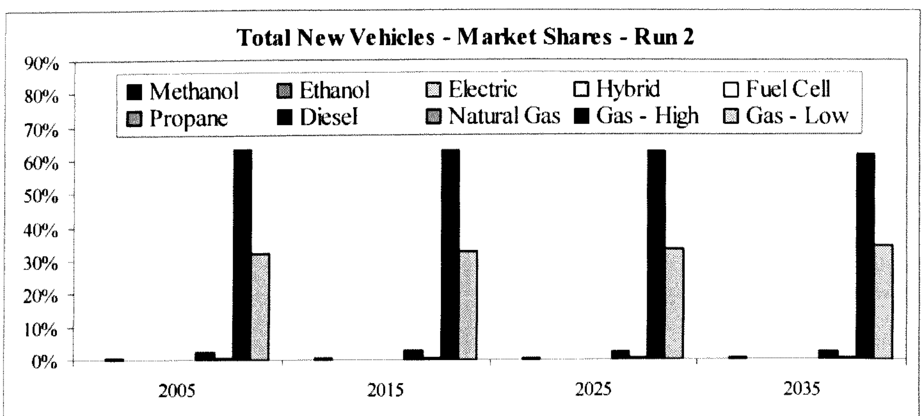

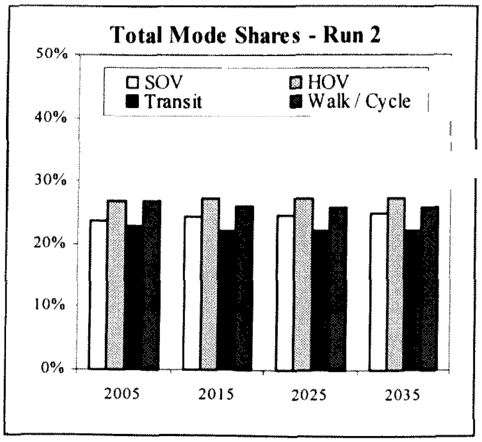

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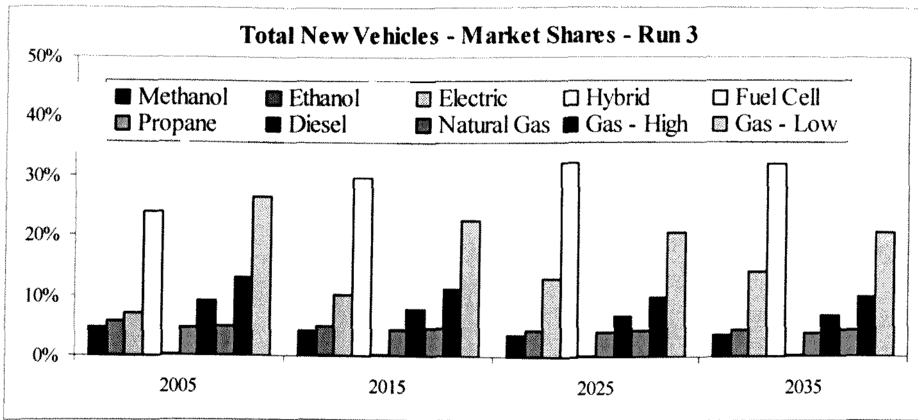

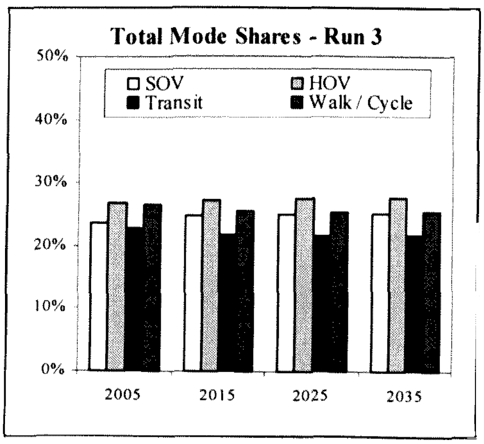

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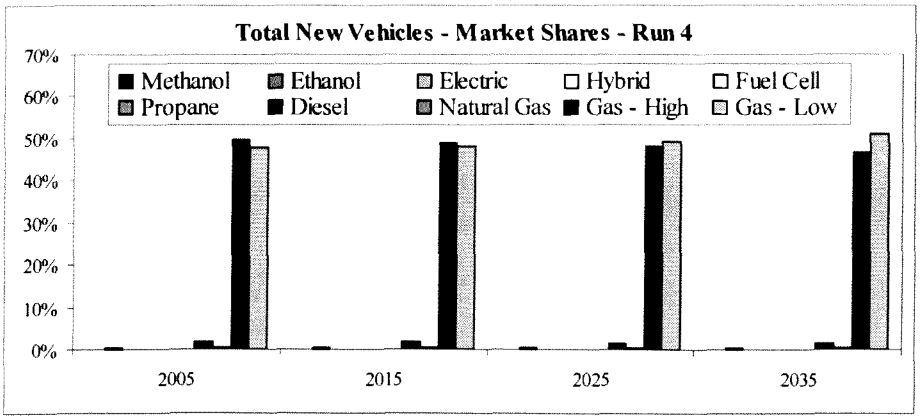

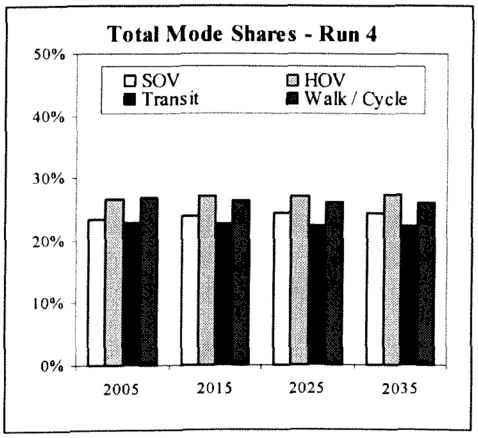

References

Asenio, J. (2002). *Transport Mode Choice by Commuters to Barcelona's CBD.* Urban Studies 31, 1881-1895.

Azar, C., and Dowlatabadi, H. (1999). *A Review of Technical Change in Assessment of Climate Policy.* Annual Review of Energy Environment 24, 513-544.

Bhat, C. (1997). *Work Travel Mode Choice and Number of Non-Work Commute Stops.* Transportation Research 31B, 41-54.

Brownstone, D., Bunch, D., and Train, K. (2000). *Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles.* Transportation Research 34B, 315-338.

Bunch, D., Bradley, M., Golob, T., and Kitamura, R., (1993). *Demand for Clean-Fuel Vehicles in California: A Discrete-Choice Stated Preference Pilot Study.* Transportation Research 27A, 237-253.

DeCanio, S., and Laitner, J. (1997). *Modeling Technological Change in Energy Demand Forecasting, A Generalized Approach.* Technological Forecasting and Social Change 55, 249-263.

Dillman, D. (1978). *Mail and Telephone Surveys: The Total Design Method.* New York: John Wiley.

Dillman, D. (1999). *Mail and Internet Surveys: The Tailored Design Method.* New York: John Wiley.

Environment Canada, (2002). *Canada's Greenhouse gas Inventory: 1990-2000.* pp 149. Retrieved September 8, 2003, from http://www.ec.gc.ca/pdb/ghg/documents/Gasinventory2000.pdf.

Energy Information Administration, (2002). *The Transportation Sector of the National Energy Modeling System: Model Documentation Report.* pp. 462. Retrieved September 8, 2003, from http://tonto.eia.doe.gov/FTPROOT/modeldoc/m070.pdf.

Energy Technology Systems Analysis Programme, (2000). *MARKAL Users. pp 1.* Retrieved September 8, 2003, from http://www.ecn.nl/unit_bs/etsap/users/main.html.

Energy Technology Systems Analysis Programme, (2002). *The MARKAL Family of Models.* ETSAP News 7, 4-6. Retrieved September 8, 2003, from http://www.ecn.nl/unit_bs/etsap/newslet/etsap77.pdf.

Espey, M. (1997). *Traffic Jam: An International Study of Automobile Travel Demand.* Papers in Regional Science 76, 343-356.

Ewing, G., and Sarigollu, E. (2000). *Assessing Consumer Preferences for Clean-Fuel Vehicles: A Discrete Choice Experiment.* Journal of Public Policy and Marketing 19, 106-118.

Fiddaman, TS. *Exploring Policy Options with a Behavioral Climate-Economy Model.* System Dynamics Review 18, 243-267.

Gabriel, S., Kydes, A., and Whitman, P. (2001). *The National Energy Modeling System: A Large Scale Energy-Economic Equilibrium Model.* Operations Research 49 (1), 14-25.

Government of Canada, (2002). *Climate Change Plan for Canada.* pp 74. Retrieved September 8, 2003, from http://www.climatechange.gc.ca/plan_for_canada/plan/pdf/full_version.pdf.

Green, D. (1988). *Survey evidence on the importance of fuel availability to the choice of alternative fuels and vehicles.* Energy Studies Review 8, 215-231.

Hensher, D. (2002). *A Systematic Assessment of the Environmental Impacts of Transportation Policy: An End-use Perspective.* Environmental and Resource Economics 22, 185-217.

Horne, M., and Rivers, N. (2002). *Translating the Performance of a Discrete Choice Model in CIMS.* Energy and Materials Research Group modeling discussion document.

Intergovernmental Panel on Climate Change (2001). *Climate Change 2001: Mitigation.* pp. 758. Retrieved September 8, 2003, from http://www.grida.no/climate/ipcc_tar/wg3/pdf/TAR-total.pdf

Jaccard, M., and Bataille, C. (2000). *Estimating Future Elasticities of Substitution for the Rebound Debate.* Energy Policy 28, 451-455.

Jaccard, M., Nyboer, J., Bataille, C., and Sadownik, B. (2003). *Modeling the Cost of Climate Policy: Distinguishing Between Alternative Cost Definitions, and Long-Run Cost Dynamics.* The Energy Journal 24 (1), 49-73.

Jaffe, A., and Stavins, R. (1994). *The energy efficiency gap: What does it mean?.* Energy Policy 22, 804-810.

Johansson-Stenman, O., and Martinsson, P. (2002). *Honestly, Why are you Driving a BMW.* Preliminary Version. pp. 17. Retrieved September 8, 2003, from http://www.handels.gu.se/econ/EEU/BMW.pdf.

Leiby, P., and Rubin, J. (2001). *Effectiveness and efficiency of policies to promote alternative fuel vehicles.* Transportation Research Record 1750, 84-91.

Louviere, J., Hensher, D., Swait, J. (2000). *State Choice Methods, Analysis and Applications.* Cambridge: Cambridge University Press.

Manne, A., and Richels, R. (1994). *The Costs of Stabilizing Global CO_2 Emissions: A Probabilistic Analysis Based on Expert Judgments.* The Energy Journal 15, 31-56.

Manski, C., and Sherman, L. (1980). *An Empirical Analysis of Household Choice Among Motor Vehicles.* Transportation Research – Part 14A, 349-366.

Manski, C. (2001). *Daniel McFadden and the Econometric Analysis of Discrete Choice.* Scandinavian Journal of Economics 103, 217-229.

McCarthy, P., and Tay, R. (1998). *New Vehicle Consumption and Fuel Efficiency: A Nested Logit Approach.* Transportation Research 34E, 39-51.

McFadden, D. (1976). *The Mathematical Theory of Demand Models.* in P. Stopher and A. Meyburg (eds.), Behavioral Travel Demand Models, 305-314, D.C. Health and Co., Lexington, MA.

McFadden, D. (2000). *Disaggregate Behavioral Travel Demand's RUM Side: A 30-Year Retrospective.* Prepared for a presentation at the International Association of Travel Behavior Analysts.

Meyer, J., and Kahn, B. *Probabilistic Models of Consumer Choice Behavior.* Pages 85-123 in the Handbook of Consumer Behavior edited by Robertson, T., and Kassarjian, H. in 1991.

MK Jaccard and Associates (1998). *Cost Curve Estimations for Reducing CO_2 Emissions in Canada: An Analysis by Project and Sector.* Report prepared for Natural Resources Canada. Retrieved September 8, 2003, from http://www.emrg.sfu.ca/EMRGweb/pubarticles/Reports for Natural Resources Canada/Costcurve.pdf.

MK Jaccard and Associates (2002). *Construction and Analysis of Regional, Sectoral, and National Cost Curves of GHG Abatement in Canada.* Report prepared for Natural Resources Canada. Retrieved from September 8, 2003, from http://www.emrg.sfu.ca/EMRGweb/pubarticles/Reports for Natural Resources Canada/Costcurve1.pdf.

Montgomery, D. (2001). *Design and Analysis of Experiments.* New York: John Wiley.

Morgan, M., and Henrion, M. (1990). *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis.* Cambridge: Cambridge University Press.

Morris, S., Goldstein, G., and Fthenakis, V. (2002). *NEMS and MARKAL-MACRO Models for Energy-Environmental-Economic Analysis: A Comparison of the Electricity and Carbon Reductions Projections.* Environmental Modeling and Assessment 7, 207-216.

Moxnes, E. (2003). *Estimating Customer Utility of Energy Efficiency Standards for Refrigerators.* Working papers in system dynamics – Department of Information Science, University of Bergen, Norway. Retrieved September 8, 2003, from http://www.ifi.uib.no/sd/workingpapers/WPSD4.03EStand.pdf.

Natural Resources Canada, (2002). *Transportation Sector 1990-2000: Transportation Explanatory Variables.* Retrieved September 8, 2003, from http://oee.nrcan.gc.ca/neud/dpa/tables/6g.xls.

Palma, A., and Rochat, D. (2000). *Mode Choice for Trips to Work in Geneva: An Empirical Analysis.* Journal of Transport Geography 8, 43-51.

Pilkington, A. (1998). *The Fit and Misfit of Technological Capability: Responses to Vehicle Emission Regulations in the US.* Technology Analysis & Strategic Management 10, 211-224.

Reckhow, K. (1994). *Importance of Scientific Uncertainty in Decision Making.* Environmental Management 18, 161-166.

Revelt, D., Train, K. (1997). *Mixed Logit with Repeated Choices: Households' Choices of Appliance Efficiency Level.* Review of Economics and Statistics.

Rivers, N, and Horne, M. (2003). *Calculation of Welfare Costs in CIMS.* Energy and Materials Research Group modeling discussion document.

Rivers, N., Jaccard, M., Nyboer, J., and Tieddeman, K. (2003). *Confronting the challenge of hybrid modeling: Using discrete choice models to inform the behavioral parameters of a hybrid model.* Accepted for publication in ACEEE, 2003 conference.

Schimmelpfennig, D. *Uncertainty in Economic Models of Climate Change Impacts.* Climatic Change 33, 213-234.

Schroeder, H., and Louviere, J. (1999). *State Choice Models for Predicting the Impact of User Fees at Public Recreation Sites.* Journal of Leisure Research 31, 300-324.

Seebregts, A., Goldstein, G., and Smekens, K. (2002). *Energy/Environmental Modeling with the MARKAL Family of Models.* Selected Papers of the International Conference on Operations Research (OR 2001), Duisburg, September 3 - 5, 2001. Retrieved September 8, 2003, from http://www.uni-duisburg.de/or2001/pdf/Sek%2002%20-%20Seebregts%20Goldstein%20Smekens.pdf.

Simon Fraser University (2001). *Ethics Review of Research Involving Human Subjects.* Retrieved September 8, 2003, from http://www.sfu.ca/policies/research/r20-01.htm.

Statistics Canada, (2001). *Census of Canada.* Retrieved September 8, 2003, from http://www12.statcan.ca/english/census01/products/standard/themes/index.cfm.

Stavins, R. (1999). *The Costs of Carbon Sequestration: A Revealed Preference Approach.* The American Economic Review 89, 993-1009.

Tisdale, M. (2003). *The Effect of Climate Policies on Local Air Pollution: Design and Canadian Application of A Modeling Tool.* School of Resource and Environmental Management: 699 report.

Train, K. (1979). *A Comparison of the Predictive Ability of Mode Choice Models with Various Levels of Complexity.* Transportation Research 13A, 11-16.

Train, K. (1985). *Discount Rates in Consumers' Energy-Related Decisions: A Review of the Literature.* Energy 10, 1243-1253.

Train, K. (1986). *Quantitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand.* Cambridge Mass., MIT Press.

Train, K. (2003). *Discrete Choice Methods with Simulation.* Cambridge University Press.

Translink (2003). *Regional Travel Survey, GVRD Residents Age 16+.* Translink Marketing Research Department, and NFO CFGroup Inc.

Transport Canada (2000). *Canadian Vehicle Survey.* Transport Canada. Retrieved September 8, 2003, from http://www.tc.gc.ca/pol/en/cvs/files/TC_2000_CVS%20Report_E.pdf.

Verbeeke, W., Ward, R., and Viaene, J. (2000). *Probit Analysis of Fresh Meat Consumption in Belgium: Exploring BSE and Television Impact.* AgriBusiness 16, 215-234.

Washbrook, K., (2002) – *Assessing the Potential for Road and Parking Charges to Reduce Demand for Single Occupancy Vehicle Commuting in the Greater Vancouver Region.* School of Resource and Environmental Management: 699 report.