ANALYSIS

The 'neighbor effect': Simulating dynamics in consumer preferences for new vehicle technologies

Paulus Mau[a,1], Jimena Eyzaguirre[a,1], Mark Jaccard[a,*], Colleen Collins-Dodd[b,2], Kenneth Tiedemann[a,1]

[a]Simon Fraser University, School of Resource and Environmental Management, 8888 University Drive, Burnaby, BC, Canada V5A 1S6
[b]SFU Business, Simon Fraser University Vancouver, 515 West Hastings Street, Vancouver, BC, Canada V6B 5K3

A R T I C L E I N F O

Article history:
Received 28 April 2007
Received in revised form 9 April 2008
Accepted 7 May 2008
Available online 28 June 2008

Keywords:
HEV
HFCV
Stated preferences
DCM
Consumer preference dynamics

A B S T R A C T

Understanding consumer behaviour is essential in designing policies that efficiently increase the uptake of clean technologies over the long-run. Expert opinion or qualitative market analyses have tended to be the sources of this information. However, greater scrutiny on governments increasingly demands the use of reliable and credible evidence to support policy decisions. While discrete choice research and modeling techniques have been applied to estimate consumer preferences for technologies, these methods often assume static preferences. This study builds on the application of discrete choice research and modeling to capture dynamics in consumer preferences. We estimate Canadians' preferences for new vehicle technologies under different market assumptions, using responses from two national surveys focused on hybrid gas-electric vehicles and hydrogen fuel cell vehicles. The results support the relevance of a range of vehicle attributes beyond the purchase price in shaping consumer preferences towards clean vehicle technologies. They also corroborate our hypothesis that the degree of market penetration of clean vehicle technologies is an influence on people's preferences ('the neighbor effect'). Finally, our results provide behavioural parameters for the energy-economy model CIMS, which we use here to show the importance of including consumer preference dynamics when setting policies to encourage the uptake of clean technologies.

1. Introduction

Policymakers committed to achieving environmental goals face significant risks in deciding among policy options, and require credible information to support the design of effective policies that minimize societal costs over the long-run. In cases where long term environmental goals are at stake, information for policymakers about the potential effects of alternative policies tends to be scarce and uncertain, and policymakers often rely on energy-economic simulation models to make the best use of limited information. To be useful to policymakers, energy-economic simulation models must provide the most realistic projections possible, based on the best available data. The model CIMS incorporates consumer behaviour in its modeling capabilities to realistically simulate policies aimed at causing profound technological change in the long-run (Jaccard et al., 2003). Over the past few years, CIMS' ability industrial steam generation (Rivers and Jaccard, 2005), residential heating (Jaccard and Dennis, 2006) and personal urban transportation (Horne et al., 2005; Rivers and Jaccard, 2005). However, a major assumption in these works is that the way in which consumers value technologies and choose among them does not change — that is, the portrayal of consumer preferences is static. The incor

each survey participant's ability to relate to the survey questions and make informed choices.

Although a survey with a full factorial design would allow for full examination between all variables, such a survey would require each participant to evaluate 729 choice sets, which is an unrealistic task to perform. Most researchers performing choice experiments thus prefer to use an orthogonal fractional factorial design. This design accommodates the representation of each level of each attribute enough times to document its individual effects, while assuming that the attributes do not interact with each other (Montgomery, 1997). Such designs have been extensively reviewed by Street et al. (2006), and have been used in previous discrete choice research pertaining to inputs for CIMS on subjects ranging from co-generation (Rivers, 2003) to transportation mode choice (Horne, 2003). For each of our surveys, we used an orthogonal fractional factorial design of 18 choice sets, representing the three levels of each of the attributes enough times to document their individual effects on consumer decisions without interactions between attributes. This number of choice sets is well within a participant's ability to provide quality answers according to a study by Hensher et al. (2001), who found that the quality of answers from choice experiments began to deteriorate after the 30th choice due to participants' loss of interest or fatigue.

The design matrix for the hybrid vehicle study is presented in Table 2, and that for the hydrogen fuel cell vehicle study is presented in Table 3. We selected the profiles of each choice set manually, based on minimum overlap of attributes in other choice sets, while taking into account the plausible combinations of attributes that a market with the new vehicle technology may experience. In both the HFCV and HEV experimental designs, the capital cost and fuel cost variables specific for the conventional vehicles, and the subsidy, cruising range, refuelling convenience, and warranty variables all had three levels: Low (0), medium (1), and high (2). In the HEV study, the subsidy, cruising range, and warranty attributes for the conventional gasoline vehicle were held constant (C) while the fuel cost variable for the HEV vehicle was linked to the fuel cost of the conventional gasoline vehicle (L) in waschoicesets. attributesfor the costvariable for the HFCV vehicle were held constant (C) in choice all sets.

Street et a.t (2006) other design that gites

For each vehicle study, the experimental design accommodated the portrayal of differences in market conditions, which would allow for the independent estimation of discrete choice models for each hypothetical market share. We treated the market share ratio (or market condition) as a blocking variable, separating the survey sample for each study into four market share groups. Each market share group was then assigned a different version of a stated preference survey reflective of their market share ratio.

Most components of the four versions of the surveys for each study were designed to be identical, including the attributes and levels in the choice sets. The key difference in the surveys administered to each market share group was the representation of their respective market share conditions. Stated preference surveys generally educate participants about the options presented to them through conceptual descriptions. In our surveys, we facilitated the process of participant education by actively engaging participants in learning about their assigned market conditions.

Consumers usually become informed about new products over time, through talking to friends, learning about them in retail outlets, and reading articles in news media and consumer publications. In the survey environment, advanced computer multimedia technology experiences comparable to those in real life can be easily created and delivered to participants in a short period and enable them to gain a good understanding of the technology, both in how the technology works and its effects on society (Peterson et al., 1997). Marketing firms use such methods experiment, and (3) informed participants about their hypothetical market condition. For example, survey participants were able to browse through a brochure (on HEVs or HFCVs, depending on their respective survey) and receive fictional appraisals of HEVs or HFCVs from different people, with variable degrees of technology enthusiasm.

3.2. Data analysis

The HEV study collected 916 completed surveys, whereas the HFCV study collected 1019. In both cases, survey participants were assigned to one of four market share groups at random, with each group receiving at least 200 completed sets of responses (3600 observations). The regional distribution of the two samples closely reflected that of Canada in 2002 in terms of population, income, age, and household size. With the exception of a slightly higher representation of women in the HFCV study than the HEV study, all other demographic characteristics and trends in vehicle ownership among market share groups in both studies match strongly, limiting the introduction of significant bias in our results.

Both vehicle studies required the estimation of four models can provide useful information, translating their outputs into parameter values for use in CIMS simulations allows for a more comprehensive and realistic simulation of policy options.

The MNL model used in this research is one of several similar

We evaluated the HEV and HFCV models' explanatory powers statistically by testing whether they are better than models with all coefficients equal to zero (null model), or models with only the alternative specific constant (restricted model) by comparing the log-likelihoods of each of these models. The log-likelihood of a model is a negative variable that approaches zero with model validity, such that a discrete choice model capable of consistently predicting the actual choice made would have a log likelihood of zero. We tested whether there are significant differences between (1) the full model and the restricted model, and (2) the full model and the null model by making use of the fact that twice the difference between the full and restricted models is chi-squared distributed, with the number of degrees of freedom equal to the number of explanatory variables in the full model minus the number in the restricted model and in the null model, respectively. Using these tests, we found that the full model for both the HEV and HFCV studies are better fits than either the restricted or null models, since twice the difference in their log likelihoods exceeded the critical value of the chi-squared

Table 5 – MNL model parameters from HFCV study

Attribute	Market share 1 (MS1) model (0.03 percent)		MS2 model (5 percent)		MS3 model (10 percent)		MS4 model (20 percent)	
	ß	t-ratio	ß	t-ratio	ß	t-ratio	ß	t-ratio
Capital cost	−1.47E−04	−18.91	−1.84E−04	−21.56	−1.76E−04	−21.42	−1.24E−04	−17.47

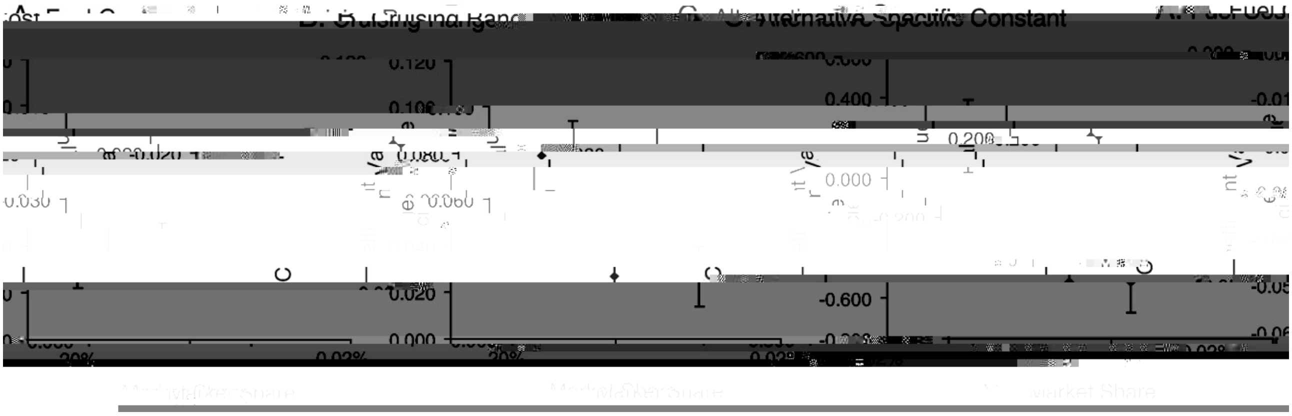

Fig. 1 – HEV significant coefficients at the 95% interval between the lowest and highest market shares (Error bars represent 95% confidence interval).

distribution with the appropriate number of degrees of freedom, at the 99.9% confidence level (Tables 4 and 5). Next, we looked at the predictive capacity of the qualitative models through the log likelihood ratio index. This index is commonly used to assess the "goodness of fit" of the models to their respective data (Train, 2003). The index ranges from 0 to 1; the value of 0 indicates that the estimated model has no predictive power, whereas a value of 1 indicates that the model can predict all consumer decisions perfectly. We found that in both the HEV and HFCV studies, this index had a value between 0.15 and 0.30 when the full models were compared with the restricted and null models, suggesting that the full models have much better predictive capacity. These values are also within the same range as the log likelihood ratio index values reported in other similar qualitative transportation models (Ewing and Sarigöllü, 2000).

4.1.1. Consumer preferences for hybrid gasoline-electric vehicles

Analysis of results from the HEV study support our hypothesis that changes in market share affect consumer behaviour and increase consumers' propensity to choose HEVs. Specifically, three attribute parameters from the HEV study exhibit trends as HEVs gain market share, between the lowest and highest market shares tested using the standard t-test at 95% confidence intervals (Fig. 1): the standardized value of the alternative specific constant (ASC), the perceived undesirability of higher fuel prices, and the perceived benefit of longer cruising range. The trends for these attributes provide strong evidence that consumer preferences for HEV are dynamic, and are a function of HEV market share. In other words, the HEV data are evidence of the neighbor effect.

The ASC captures the additional perceived benefits or costs associated with conventional gasoline vehicles over HEVs due to attributes not considered in the choice experiment. We found that with an increasing HEV market share from 0.03% to 20%, the value of attributes explained by the ASC declines (Table 6). This trend suggests that consumers view conventional gasoline vehicles as becoming less desirable with increases in HEV adoption, all else being equal. Factors such as performance, reliability, and safety of HEVs could partly explain this trend. These are factors that consumers may take into account in their vehicle purchase decisions (Horne et al., 2005; Ewing and Sarigöllü, 2000), which we did not explicitly model in this study.

Aside from implications related to the ASC, Table 6 also indicates that as the market share of HEVs increases from 0.03% to 20%, higher fuel prices becomes less of a concern, and

whereas in the HEV study respondents might have had some information on the negative attributes associated with HEVs.

The dominance of the ASC for HFCVs could reflect the potential for dramatic switches to this vehicle technology, once it has attained a given level of development and acceptability. Christensen described the commercialization of some disruptive technologies in the computing industry, and explained how established companies can fail to predict the mainstream appeal of disruptive technologies, since these technologies tend to satisfy only niche market segments at the outset (Christensen, 1997; Bower and Christensen, 1995). By definition, disruptive technologies present a set of attributes that existing customers might not value initially. However, improvements in valued and new attributes can rapidly match and outpace customers' demands, making it possible for the new technology to penetrate the primary market. The potential for this phenomenon to occur with (hydrogen) fuel cell vehicles might explain why established vehicle manufacunderestimate the penetration of new technologies, such as hybrid gasoline-electric vehicles.

5. Conclusions

This research has demonstrated that consumers' preferences in choosing between conventional and new technologies can change with market conditions. The importance that consumers

Rivers, N. 2003. Behavioural realism in a technology explicit energy-economy model: The adoption of industrial cogeneration in Canada. Master's Thesis. School of Resource and Environmental