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Consumer preferences for alternative fuel vehicles: Comparing a utility maximization and a regret minimization model

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HIGHLIGHTS

- Utility- and regret-based models of preferences for alternative fuel vehicles.
- Estimation based on stated choice-experiment among Dutch company car leasers.
- Models generate rather different choice probabilities and policy implications.
- Regret-based model accommodates a compromise-effect.

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ABSTRACT

This paper presents a utility-based and a regret-based model of consumer preferences for alternative fuel vehicles, based on a large-scale stated choice-experiment held among company car leasers in The Netherlands. Estimation and application of random utility maximization and random regret minimization discrete choice models shows that while the two models achieve almost identical fit with the data and differ only marginally in terms of predictive ability, they generate rather different choice probability-simulations and policy implications. The most eye-catching difference between the two models is that the random regret minimization model accommodates a compromise-effect, as it assigns relatively high choice probabilities to alternative fuel vehicles that perform reasonably well on each dimension instead of having a strong performance on some dimensions and a poor performance on others.

1. Introduction

Consumer preferences are a critical factor in the development of successful alternative fuel vehicles, or from here on AFVs (e.g., Molin, 2005; Struben and Sterman, 2008; Huijts et al., 2012). For this reason a wide range of recent studies have sought to explore these preferences in the context of a range of AFV-technologies (e.g., Potoglou and Kanaroglou, 2007; Caulfield et al., 2010; Dodson et al., 2010; Erdem et al., 2010; Ozaki and Sevastyanova, 2011). As a recent overview-study by Roche et al. (2010) suggest, many studies into consumer preferences for AFVs rely on the estimation and subsequent application of discrete choice models on stated choice-data. Moreover, what is also shared by the large majority of these and other studies into consumer preferences for AFVs is that they adopt a particular behavioral model for the analysis of observed choices: that of utility maximization. More particularly, almost without exception estimated discrete choice models take on the form of so-called random utility maximization (RUM) models with linear-in-parameters utility functions, such as RUM-based (Mixed) Multinomial Logit models, Nested Logit models or Probit models (see Ben-Akiva and Lerman, 1985;Train, 2009, for in-depth discussions of the RUM-model of consumer preferences).

Notwithstanding the obvious elegance and tractability of these models as exhibited in a wide range of studies in fields as diverse as marketing, transportation and environmental economics, the almost exclusive focus on RUM as a model of behavior is not in line with recent trends in adjacent fields, where non-RUM models have gained popularity lately as possibly more behaviorally realistic alternatives to RUM (e.g., Arentze and Timmermans, 2007; Hensher, 2010). A micro-simulation study by Mueller and de Haan (2009) also show how capturing so-called bounded rational behavior may lead to new insights into consumer preferences for AFVs. Although this latter study, like most others in the field, uses a linear-in-parameters RUM-based decision-rule, it does allow for insights from non-utilitarian behavioral models (such as prospect theory) to co-determine consumer preferences and choices.

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Motivated by this recent interest in non-RUM decision-rules this paper proposes to use a so-called random regret minimization-based behavioral model that has recently been successfully introduced in a range of travel demand studies. This so-called RRM-model (Chorus, 2010) postulates that consumers aim to minimize regret, rather than maximize utility, when making decisions. The RRM-model (its Multinomial Logit-form) distinguishes itself from other non-RUM models in terms of its usability: it features closed-form formulations of choice-probabilities and can be easily estimated using readily available discrete choice-software. The model has been successfully tested empirically by various researchers in the context of a wide range of travel demand related choice-contexts, but also in the context of choices made by politicians among policy options and choices made by visitors of dating websites among dating profiles (see Chorus, 2012, for an overview of the empirical evidence). The model is based on the behavioral notion that regret emerges when a non-chosen alternative outperforms a chosen one in terms of one or more features. It should be noted here that it is well known in the field of consumer research (e.g., Zeelenberg and Pieters, 2007) that the minimization of regret is a particularly important determinant of consumer behavior when choices are perceived by the decision-maker as important and difficult, and relevant to his or her social peers. Intuitively, these conditions would seem to hold in the context of buying a new car. Furthermore, the regret minimization model in a conceptual sense puts extra 'weight' on situations where a considered alternative performs relatively poorly compared to the competition. It may therefore be a particularly relevant model in the context of AFV-adoption given that AFVs tend to be outperformed by conventional fuel vehicles on important attributes such as price and driving range. As such it seems worthwhile to use the newly developed RRM-discrete choice model and compare it with its linear-additive RUM-counterpart in the context of consumer preferences for AFVs.

There has been one other study that has compared the RRM-model with its RUM-counterpart in the context of stated choices for AFVs (Hensher et al., 2011). This study differs from the Hensher et al. study on the following three dimensions, aside from the difference in geographical focus and timing of the data collection (Australia, 2009 versus The Netherlands, 2011). First, whereas Hensher et al. (2011) focus on preferences for private cars, this paper focuses on company car-leasers and their preferences for company cars. This difference is non-trivial in light of the fact that in many countries (such as in The Netherlands) the government aims to influences vehicle type-choices made by company car-leasers by means of specific tax-related incentives. Second, in contrast with Hensher et al. (2011) we perform an out-of-sample validation exercise to test and compare the predictive ability of estimated RRM- and RUM-models. Third, whereas Hensher et al. (2011) apply the estimated RRM- and RUM-models by deriving and interpreting elasticities for various attributes, this paper uses choice probability simulations to highlight the differences between the RRM- and RUM-models. This latter method allows us to highlight one of RRM's most salient properties, being its ability to capture so-called compromise effects (more on these effects can be found below).

The remainder of this paper is structured as followed. Section 2, drawing from earlier work on RRM, presents the RRM-model as an alternative to the conventional (linear-additive) RUM-model. The data-collection is presented in Section 3. Section 4 discusses model estimation and validation, followed by choice probability simulations presented in Section 5. Conclusions are derived in Section 6.

Before we move on to the next section, we find it important to note up front that it is certainly not our aim to try and select any one of the two models under comparison as being in any way superior. Such a conclusion would be highly speculative in light of the fact that we based our comparison on only one dataset. We merely wish to highlight the added behavioral and policy-related insights that may be gained by *jointly*[1] using choice models that are based on different behavioral premises. We ask the reader to keep this in mind when reading the remainder of this paper.

2. A random regret minimization-based discrete choice model

This section draws from Chorus (2012) and Thiene et al. (2012). Assume the following choice situation: a decision-maker faces a set of J alternatives or choice options, each being described in terms of M attributes or features that are comparable across alternatives. The focus is on predicting the choice probability for an alternative i from this set. First note that a conventional, linear-in-parameters utilitarian specification would assign the following utility to alternative i: $V_i=\sum_{m=1..M}\beta_m x_{im}$. Subsequently, independently and identically distributed (i.i.d.) Extreme Value Type I-distributed errors (representing 'white noise') are added to the utilities of all alternatives in recognition of the fact that the researcher is unable to faultlessly assess the exact levels of utility. Note that this distribution resembles the normal distribution, but has fatter tails. This implies the following Multinomial Logit (MNL) formulation of the resulting choice probability (McFadden, 1974): $P_i=\exp(V_i)/\sum_{j=1..J}\exp(V_j)$.

The RRM-based model postulates that, when choosing between alternatives, decision-makers aim to minimize anticipated random regret. The level of anticipated random regret that is associated with the considered alternative i is composed of an i.i.d. random error ε_i, which represents unobserved heterogeneity in regret and whose negative is Extreme Value Type I-distributed, and a 'systematic' or 'observable' regretR_i. Systematic regret is in turn conceived to be the sum of all so-called binary regrets that are associated with bilaterally comparing the considered alternative with each of the other alternatives in the choice set. The level of binary regret associated with comparing the considered alternative with another alternative j is conceived to be the sum of the regrets that are associated with comparing the two alternatives in terms of each of their M attributes. This attribute level-regret in turn is formulated as follows (see Chorus, 2010, for an argumentation behind this particular function form of the regret-function): $R^m_{i\leftrightarrow j}=\ln(1+\exp[\beta_m\times(x_{jm}-x_{im})])$. This formulation implies that regret is close to zero when alternative j performs (much) worse than i in terms of attribute m, and that it grows as an approximately linear function of the difference in attribute-values in case i performs worse than j in terms of attribute m. In that case, the estimable parameter β_m (for which also the sign is estimated) gives the approximation of the slope of the regret-function for attribute m. See Fig. 1 for a visualization of this formulation of attribute-level regret (for the situations where $\beta_m=1$, 2 and 3, respectively).

Systematic regret can then be written as: $R_i=\sum_{j\neq i}\sum_{m=1..M}\ln(1+\exp[\beta_m\times(x_{jm}-x_{im})])$. Acknowledging that minimization of random regret is mathematically equivalent to maximizing the negative of random regret, choice probabilities may be derived using a variant of the well-known multinomial logit formulation: the choice probability associated with alternative i equals $P_i=\exp(-R_i)/\sum_{j=1..J}\exp(-R_j)$.

Aside from their obvious similarities (such as logit-type choice probabilities) the two modeling perspectives exhibit a number of important differences. We briefly highlight three of those below;

[1] An example of joint usage of the two modeling perspectives would be to compare the effects of policy implications as predicted by both models, and to subsequently treat the two sets of model outcomes as upper and lower bounds of expected policy impacts.

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