Stated choices and benefit estimates in the context of traffic calming schemes: utility maximization, regret minimization, or both?

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Abstract

This paper proposes a discrete mixture model which assigns individuals, up to a probability, to either a class of random utility (RU) maximizers or a class of random regret (RR) minimizers, on the basis of their sequence of observed choices. Our proposed model advances the state of the art of RU-RR mixture models by i) adding and simultaneously estimating a membership model which predicts the probability of belonging to a RU or RR class; ii) adding a layer of random taste heterogeneity within each behavioural class; and iii) deriving a welfare measure associated with the RU-RR mixture model and consistent with referendum-voting, which is the adequate mechanism of provision for such local public goods. The context of our empirical application is a stated choice experiment concerning traffic calming schemes. We find that the random parameter RU-RR mixture model not only outperforms its fixed coefficient counterpart in terms of fit—as expected—but also in terms of plausibility of membership determinants of behavioural class. In line with psychological theories of regret, we find that, compared to respondents who are familiar with the choice context (i.e. the traffic calming scheme), unfamiliar respondents are more likely to be regret minimizers than utility maximizers.

Keywords: Random Regret Minimization, Random Utility Maximization, Discrete choice experiment, Latent classes, Traffic calming schemes

Research Highlights:

- We estimate a behavioural latent class comparing two choice paradigms (RR and RU).
- We explore the determinants of being best described by RR or RU choice behaviour.
- We derive adequate welfare estimates for this context of mixed choice behaviours.
- We associate familiarity with the choice context with utility maximization.
- Respondents unfamiliar with the choice context are likely to adopt regret minimization.

1. Introduction

As the common place saying goes, a glass holding some wine can be perceived—depending on the perspective of the onlooker—either as partly ‘empty’ or as partly ‘full’. The potential consequences of these subjective and different views of reality may well extend to choice behaviour. Such consequences, however, tend to be systematically under-investigated. Especially so in empirical studies based on discrete choice models where the well-established paradigm of random utility (RU) maximization dominates. This paper moves from the premises that both the above views can be argued to underlie the rationale for deliberative choice. As a practical consequence, they both should be systematically accommodated in empirical analysis of choice outcomes.

A decision-maker who is inclined to see the glass partly ‘empty’ might be more inclined to focus on regret minimization, rather than focussing on utility maximization. Therefore, when a series of alternatives are evaluated by a subject with such a behavioural inclination, some evidence of this regret minimizing behaviour should be detectable in the sequence of observed choices. Regret minimization leads to a systematically different pattern of choices from those made by subjects who strictly comply with the received view of utility maximization in their choice behaviour.

Beyond pessimism, there may be many other reasons that may induce decision makers to engage in regret minimization, including having achieved an already satisfactory level of utility as provided by the status quo after a long and costly search. This would be a ‘satisficing’ approach that might be attractive to those who wish to avoid the risk of change or the search cost involved in a new choice. So, extreme risk aversion or perception of unusually high information search cost can also motivate random regret (RR). Further examples include those who feel their choices will be judged by others with potentially different values. Or those who feel that vulnerable dependents, such as young children or elderly, might suffer as a consequence of their decision-making (Zeelenberg and Pieters, 2007). All such subjects may be more inclined to choose trying to minimize expected regret, rather than to seek utility maximization.

Regardless of the motivating factors, the availability of empirically tractable models of RR choice behaviour is desirable to practitioners. Recent work by Chorus (2010) provide analysts with exactly such a category of choice models, conveniently framed around the popular logit specification for the computation of choice probabilities. Given the availability of empirically tractable minimum regret models of discrete choice, in this paper we investigate the implications of simultaneously modelling two mutually exclusive rationales for choice behaviour: (*i*) the standard RU maximization and (*ii*) the much more seldom employed RR minimization. That is, we hypothesize that while the sequence of choices made by some decision-makers are more likely to result from regret minimization behaviour, those made by others are instead more likely to result from utility maximization behaviour.

Such heterogeneity in choice behaviour is modelled by assuming the existence of two behaviourally different latent classes, one including regret minimizers and the other utility maximizers. This gives rise to a probabilistic decision process similar in form to the conventional panel latent class (LC) models for discrete preference heterogeneity. In our model, instead classes describe specific decision paradigms or heuristics. Analogous approaches based on behaviourally separate Latent classes have been used by others (Scarpa et al., 2009; Hensher and Greene, 2010; Hess et al., 2012; Campbell et al., 2012) and are collectively called probabilistic decision processes (PDPs).

By doing so our study moves away from the conventional, and behaviourally quite restrictive, assumption that only one of the two paradigms (utility or regret) would be the best representation for all choices observed in the sample (e.g., Chorus et al., 2011; Hensher et al., 2013; Chorus, 2012; Thiene et al., 2012; Boeri et al., 2012a,b; Chorus and Bierlaire, 2013; Kaplan and Prato, 2012). Furthermore, we make three novel contributions compared to a recent similar study by Hess et al. (2012), which is the only other study we know of that accommodates regret minimization and utility maximization by means of latent classes.[1] First, we empirically study the determinants for

[1]Note that the conventional approach to applying latent class models in transportation is to assume that classes differ in terms of preference intensities, in the form of estimable parameters which differ between preference classes (e.g Olaru et al., 45; Beck et al., 2013; Vij et al., 2013).

both choice behaviours by means of a membership function explaining membership probability to both choice behaviours. Second, we overlay a characterization of random preference heterogeneity to each specific choice behaviour. By doing so we achieve the desirable outcome of simultaneously accounting for both taste and choice behaviour heterogeneity in one single model that combines a discrete mixing process (across regret and utility classes) and a continuous mixing process (across coefficient values within each behavioural class). Third, we evaluate the user benefits or welfare effects associated with selected public programs (in particular: traffic calming schemes) under the proposed model. More specifically, we suggest an estimation of the monetary value predicted to obtain a fifty percent support of a proposed traffic calming scheme.

For the purpose of illustration of this method we explore choice data from a classic experiment on traffic calming schemes conducted in the year 2000. See Barbosa et al. (2000) for a relevant previous study on traffic calming which was published in this journal; while that paper focuses on the impact of traffic calming on speed profiles, our study concerns preferences for different alternative specifications of such schemes. We note that the data used here were not previously used except for the technical report to the funding agency, while results from its twin study based on other Northern England locations was published in 2002 (Garrod et al., 2002). The population under study were those that at the time resided in Sherburn in Elmet, a rural town in Northern England which is crossed by trunk road traffic. Residents of these types of rural towns typically suffer the negative consequences from through traffic and enjoy little of the benefits since most vehicles tend not to stop in town. Long-haul freight transport on wheels across England and Scotland often induces heavy vehicle traffic along these trunk roads and as a consequence they exacerbate the production of negative local externality. Specifically the experiment concerned separate features of a traffic calming project designed to reduce the negative consequences for residents of the traffic through the town, such as excessive speed, community severance and noise.

Importantly, we wish to state up front that our aim is not to compare the RR and RU paradigm. Many recent papers have provided such comparisons, and the over-all result is becoming increasingly clear. Chorus et al. (working paper) present a critical overview of more than forty empirical comparisons between RR and RU: differences in model fit between the RR and RU model are generally small but statistically significant at conventional sample sizes, the RR model outperforming linear-additive RU formulations in about 50% of cases. Also differences in predictions for out of sample performance are found to be small. Interestingly, though, differences in terms of elasticities and in terms of choice probabilities for individual choice situations can be quite large. As a consequence, the two model types can lead to markedly different policy implications Chorus et al. (working paper). This paper does not aim to provide yet another comparison of the two model types. Rather, we wish to show how the two behavioural assumptions can be used jointly in an integrated model, while allowing for heterogeneity within each behaviour, regret or utility based.

In the rest of the paper we proceed by first discussing in Section 2 the main features of the two choice behaviours. We develop the discussion in relation to the existing literature and describe the model with which we propose to investigate the discrete mixing of the two behaviours, focussing on our effort to (i) explore the determinants of membership into the two behavioural classes, and (ii) allow for taste heterogeneity within behavioural classes. Finally, we describe how to derive welfare measures about the provision of a local public good from our modelling approach.

The survey and data we use to empirically illustrate the approach are presented and discussed in Section 3 and the results of our estimations are in Section 4. In Section 5 we illustrate the welfare effects evaluations associated with selected public programs and Section 6 summarizes our findings and reports our conclusions.

2. Methods

From the perspective of the researcher who intends to account for different choice behaviours (or paradigms[2]) by using PDP models and including the self-evident issue of heterogeneous taste across individuals within these processes, three steps are required. The first step involves the

[2]In this paper we use the terms 'choice paradigms', 'decision processes, 'choice behaviour' interchangeably.

definition of probabilistic choice models conditional on the choice paradigms giving rise to the observed choice processes. This step explains how choice is conducted if the subject is acting according to each of the choice paradigms, up to a given probability. Well established models exist for the practical implementation of this step when subjects are acting under utility maximization. These are not as common for regret minimization, despite its implementation only requires minimal adaptation. The second step deals with the probabilistic allocation of subjects to specific paradigms and hence decision processes. This step simply allocate the subject with a given degree of probability to each of the choice paradigms on the basis of the observed choice sequence. We implement this here using the conventional finite mixing between processes by means of a behavioural latent class approach. Finite mixing of decision processes is a well-established approach to model latent higher order choice behaviours based on, for example, attribute processing, elimination by aspect and other behavioural paradigms. This approach is probabilistic and can be contrasted with the deterministic allocation of respondents to different utility specifications based on respondents self-reports (Hensher et al., 2005; Campbell et al., 2008). The third and final step, which is novel in this context and is required for realism, is allowing for preference heterogeneity across respondents within choice behaviours. This is addressed here by introducing continuous mixing of preferences within latent groups (Bujosa et al., 2010; Hensher et al., 2012a; Boeri, 2011). In what follows, we tackle in some detail each of these steps.

2.1. Choice modeling under Random Utility Maximization

The aim of this section is to formally describe a model of choice for the process followed by an individual in choosing her favourite traffic calming alternative i from a set of $j \in J$ mutually exclusive alternatives offered in each choice task of our experiment. Typically, choice experiments use a balanced panel of T observed choices. So, each respondent is given T such choice tasks to perform. In our empirical case we will consider the situation in which a subject n has to choose between J traffic calming alternatives, in a repeated sequence of T choice tasks, each of which is denoted by $t \in T$ and selects the favourite alternative by utility (U_{nit}) maximizing. According to the conventional RU maximization (henceforth RU) approach (Thurstone, 1927; Manski, 1977), respondents are thought of as selecting the alternative that maximizes their (expected) utility. Only a component of utility—the indirect utility—is observable to researchers and can hence be described by observable attributes. Therefore, from the analyst's perspective the focus is placed on the indirect component of utility, $V(\beta, x_{nit})$, that each alternative i brings to the respondent n in choice task t. The total utility of each alternative includes a random component, and it is represented by the function:

$$U_{nit} = V(\boldsymbol{\beta}, \mathbf{x}_{nit}) + \epsilon_{nit}, \tag{1}$$

where $\mathbf{x}_{nit}$ is a vector of $k \in K$ attribute levels and dummy variables describing the alternatives, $\boldsymbol{\beta}$ is a vector of utility coefficients to be estimated and ϵ is the unobservable and idiosyncratic (or indirect) component of total utility, which is assumed to be randomly distributed according to an *i.i.d.* Gumbel process.

Given the utility function of equation (1) and the associated assumptions on the error term, the probability for individual n of choosing alternative i over any other alternative j in the choice set t is represented by a RU - multinomial logit (RU-MNL) model McFadden (1974) is:

$$\Pr^{RU}_{nit} = \frac{e^{\boldsymbol{\beta}'\mathbf{x}_{nit}}}{\sum_{j=1}^{J} e^{\boldsymbol{\beta}'\mathbf{x}_{njt}}}. \tag{2}$$

This is the very familiar logit probability of choice that McFadden (1974) showed to be consistent with a choice process guided by utility maximization.

2.2. Choice modeling under Random Regret Minimization

A model of probabilistic choice under RR minimization (henceforth RR) was implemented as a modification of equation (2) in transportation by Chorus (2010).

In our context the RR approach postulates that, when choosing between alternatives, decision makers select the traffic calming scenario that minimizes anticipated regret as represented by the alternatives in each choice task. Conceptually, the level of total anticipated regret that is associated with each alternative i is composed of two parts, similarly to what described above for the utility maximization approach. There is a systematic or observable part of regret, and an unobservable idiosyncratic component, which is assumed to behave in a stochastic fashion.

The 'systematic' component of regret associated with respondent n choosing alternative i in choice occasion t can be written as a function of the departures from the levels of each of the m attributes describing the traffic scenario i and the levels of corresponding attributes used in all other scenario descriptions $j \neq i$:

$$R_{nit} = \sum_{j \neq i} \sum_{m=1...M} \ln\Big(1 + \exp(\theta_m \delta_{ij})\Big), \text{ where } \delta_{ij} = x_{njmt} - x_{nimt}. \tag{3}$$

By inspection of equation 3 one can identify the crucial difference between RR and linear-additive RU models: RR postulates that bilateral comparisons with all other alternatives in the choice set have an influence on the regret associated with a considered alternative. As discussed in greater detail in many of the papers on RR cited in the introduction, this dependency of choice probability on attribute-levels of competing alternatives causes the RR model to exhibit semi-compensatory behaviour and choice set composition (or context) effects.[3]

Note that the determinants of the above systematic regret measure are observed by the researcher, but the idiosyncratic component ε_{nit} is not. Assuming that $-\varepsilon_{nit}$ is additive to the observable component R_{nit} and distributed *i.i.d.* Gumbel leads to a logit choice probability based on total anticipated regret. This represents the random component of anticipated regret unobservable to the analyst. Once combined with the systematic component of regret denoted by R_{nit}, this gives total random anticipated regret:

[3]See Chorus (2010) for a complete derivation and description of the model, and see Chorus and Bierlaire (2013) for a description and empirical analysis of how RR captures a context effect known as the compromise effect.

$$\tilde{R}_{nit} = R_{nit} + \varepsilon_{nit} = \sum_{j \neq i} \sum_{m=1...M} \ln\left(1 + e^{\theta_m \delta_{ij}}\right) + \varepsilon_{nit} \tag{4}$$

Given the systematic regret described in equation (3), and acknowledging that minimization of regret is mathematically equivalent to maximizing the negative of the regret, the probability for individual n of choosing alternative i over any other alternative j in the choice set can be represented by the well-known multinomial logit formula for the integral over a Gumbel distributed $-\varepsilon_{nit}$, or:

$$\Pr_{nit}^{RR} = \frac{e^{(-R_{nit})}}{\sum_{j=1}^{J} e^{(-R_{njt})}}. \tag{5}$$

At this point it is important to note that the notion of regret on which the RR model is built differs from the notion of regret in models of risky decision-making (e.g. Bell, 1982; Loomes and Sugden, 1982; Quiggin, 1994; Starmer, 2000; Loomes, 2010; Bleichrodt et al., 2010; Baillon et al., 2013). That is, RR models postulate that regret may also exist when the performance of choice alternatives (as described by attribute levels) is fully known by the decision-maker (i.e., in the absence of risk or uncertainty). In RR models regret arises from the situation where a decision-maker has to put up with non-ideal performance on some attributes, in order to achieve a good performance on others. In other words, it is the trade-off between different attributes which causes regret. In contrast, models of risky choice that are built on the notion of regret (such as Regret Theory) assume that regret is caused by the fact that the decision-maker only knows the performance of alternatives up to a probability. Therefore an alternative that performs worse than another on certain attributes might be chosen. Regret Theory, related theories and models of risky choice postulate that without uncertainty or risk there can be no regret. This is a fundamental contrast with the behavioural premises underlying RR. Nonetheless, what the two paradigms have in common is the notion that choices are (co-)determined by the wish of the decision-maker to avoid the situation where one or more non-chosen alternatives outperform at least in some respect the selected one: it is the comparison-aspect, and the focus on negative outcomes, which is the commonality between RR minimization models and Regret Theory.

Before moving to our description of how we model choice under co-existence of RU and RR heuristics in the same population, it is useful to discuss to what extent the two paradigms actually result in different behaviours (choice probabilities for alternatives in choice tasks).

This question can be answered along two lines: a first approach is using synthetic data, where the same parameters are used for predicting RU and RR choice probabilities. See for example Chorus (2010) for this approach. However, since in reality the two paradigms are usually found to result in different parameters (for example: the magnitude of RR parameters decreases as the choice set gets bigger, due to the summation of strictly positive terms in the regret function), the usefulness of this numerical approach, which uses the same set of parameters, is limited.

Various papers have explored to what extent choice probabilities generated by estimates from the two models differ. To cite one example, Chorus et al. (2013) analysed preferences of company car users in terms of alternative fuel vehicles. Despite that the estimated RU and RR models achieved a very similar fit with the data, when both models were used to predict market shares of different alternatives in a hold-out sample, differences between RU and RR in terms of predicted choice probabilities were often large: in 26% of the cases the difference between the choice probabilities predicted by RR and RU was larger than 5 percentage points and in about 4% of the cases it was 10 percentage points or more. In about 7% of choice situations, the RR and RU model identified different car-types as the winner in their choice set.

2.3. Finite mixing of choice behaviours

Given that respondents to our survey can choose according to either a RU or a RR paradigm, we assume that within any given sample of respondents, we observe a mixture of panels of t observed choices. Each of the total n panels can be assigned—up to a probability—to one of the two latent choice-behaviour groups. One group produces responses by systematically engaging in a choice behaviour more consistent with RU, while the other appears more consistent with RR. We hence propose below a discrete mixing model between the two behavioural classes.

As mentioned in the introduction, most previous studies estimate two separate MNL models, one for RR and one for RU, and then proceed to compare the two models. In this study we follow Hess et al. (2012) and use a behavioural latent class approach. This approach is extended here to investigate the determinants of class—and hence of choice behaviour. Specific correlations between measurable socio-economic co-variates and types of choice behaviour are desirable for validating the estimation results.

To investigate the latent mixture of decision processes we employ the LC modeling approach. This falls under the broader category of Mixed Logit models McFadden and Train (2000) and it is characterised by a discrete as opposed to continuous mixture of choice probabilities, which takes place over a finite number of homogeneous groups (classes). Each of these internally displays homogeneous choice behaviour. The mixing distributions $f(\boldsymbol{\beta})$ and $g(\boldsymbol{\theta})$ are therefore discrete with the random parameter vectors $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ taking on a finite set of distinct values.

In the traditional RU specification of the LC choice model with C classes, the probability of observing a sequence of T_n choices by respondent n is based on a conventional RU framework of the conditional logit model (equation 1). Conditional on being in class $c \in C$, and therefore using coefficient vector β_c, the probability of a choice sequence is defined as:

$$\Pr\left(y_n|c\right) = \prod_{t=1}^{T_n} \frac{e^{\left(V_{nit}\right)}}{\sum_{j=1}^{J} e^{\left(V_{njt}\right)}} = \prod_{t=1}^{T_n} \frac{e^{\left(\beta_c' \mathbf{x}_{nit}\right)}}{\sum_{j=1}^{J} e^{\left(\beta_c' \mathbf{x}_{njt}\right)}}. \tag{6}$$

Membership probabilities for each latent class c are defined according to a multinomial logit process as:

$$\pi_c = \frac{e^{\alpha_c + \gamma_c' \mathbf{z}_n}}{\sum_{c=1}^{C} e^{\alpha_c + \gamma_c' \mathbf{z}_n}}, \tag{7}$$

where $\mathbf{z}_n$ is a vector of co-variates characterizing respondent n, and $\boldsymbol{\gamma}$ is the vector of associated parameters subject to estimation, while α_c is a class-specific constant. In estimation, for identification purposes only $C-1$ set of coefficients can be independently identified. For one arbitrary class c the vector $\alpha_c; \boldsymbol{\gamma}_c = 0$, so that for this c class $e^0 = 1$ and its class membership probability is:

$$\pi_c = \left[1 + \sum_{c=1}^{C-1} e^{\alpha_c + \gamma_c' \mathbf{z}_n}\right]^{-1}, \tag{8}$$

The unconditional probability of a sequence of choices can be derived by taking the expectation over all the C classes:

$$\Pr(y_n) = \sum_{c=1}^{C} \pi_c \prod_{t=1}^{T_n} \frac{e^{\left(\beta_c' \mathbf{x}_{nit}\right)}}{\sum_{j=1}^{J} e^{\left(\beta_c' \mathbf{x}_{njt}\right)}}. \tag{9}$$

The above equation represents the choice probability as described by a LC model within the RU framework. Since our objective is to consider the contribution of choices conducted under both the RU the RR frameworks, it is necessary to extend equation (9) to account for the RR minimization. This can be achieved by defining a two class LC model in which the choice probability within each class—$\Pr(y_n|c)$—is defined by one of the two choice paradigms under consideration (i.e. RU from equation 2 and RR from equation 5). Putting together the two sources of choice behaviour with their respective membership probabilities we obtain the following unconditional probability for a sequence of T observed choice responses:

$$\Pr(y_n) = \pi_V \prod_{t=1}^{T_n} \Pr_{nit}^{RU} + \pi_R \prod_{t=1}^{T_n} \Pr_{nit}^{RR}, \tag{10}$$

where $0 \leq \pi_V \leq 1$ and $\pi_R = (1 - \pi_V)$ are the membership probabilities for the RU class and the RR class, respectively. The first term in equation (10) is described by a RU-MNL and the second term is determined by a RR-MNL (see equations 1–5).

2.4. Taste heterogeneity within choice behaviours

Within each behavioural class it is reasonable to expect a degree of heterogeneity of taste. Apart from extending this model to the investigation of determinants of class membership, we also allow for taste heterogeneity within each class. Since these are behavioural classes, and not taste heterogeneity classes, ignoring unobserved taste heterogeneity would imply a potential specification bias as we know from the overwhelming evidence reported in the literature that such heterogeneity is likely to be present in most choice data.

In order to extend equation (10) to a specification accounting for such a pervasive phenomenon we also estimate a model which addresses continuous heterogeneity of taste across respondents within the same choice paradigm class (LC-RPL model) (Bujosa et al., 2010; Hensher et al., 2012b; Hess et al., 2012). The resulting unconditional choice probability can be described by the following random parameter logit model:

$$\Pr(y_n) = \pi_V \int_{\beta} \prod_{t=1}^{T_n} \Pr_{nit}^{RU} f(\boldsymbol{\beta})\, d\boldsymbol{\beta} + \pi_R \int_{\theta} \prod_{t=1}^{T_n} \Pr_{nit}^{RR} g(\boldsymbol{\theta})\, d\boldsymbol{\theta}, \tag{11}$$

in this model the first class is described by a RU-RPL and the second class is based on a RR-RPL. Normal distributions are assumed for all random parameters in each class, therefore in $f(\boldsymbol{\beta})$, $\beta \sim N(\mu, \sigma^2)$, and $g(\boldsymbol{\theta})$, $\theta \sim N(\xi, \omega^2)$. These probability integrals do not have close-form and they are simulated in estimation.

2.5. Welfare measures in the mixture paradigm model

While the derivation of welfare measures from RU models is well known and underpins much of the non-market literature based on this paradigm, the use of the regret minimization approach poses specific challenges. In the RR paradigm there is no immediate close-form solution for microeconomic concepts such as compensating or equivalent variation, nor is there one for consumer surplus. The logsum can be computed, but unlike in the RU case (Train, 2009), the exact microeconomic meaning of this value is unclear (Chorus, 2012; Boeri et al., 2012a). It is nevertheless possible to use the coefficient estimates to carry out some sample-based simulations to find the predicted proportion of the sample that would support a given policy scenario at a given cost. In our local public good provision context of a traffic calming scheme, the quantity of interest is the maximum amount that still triggers majority support by residents for a given scheme (e.g. 50 percent). This would be an accurate model for the outcome of a local referendum poll, for example. We propose this amount as an estimate of the welfare change associated with a given proposal and specific to those adopting that choice paradigm.[4]

In practice this involves the computation of posterior coefficients for each individual respondent in the sample, conditional on the pattern of observed choices, which can be achieved by applying Bayes' theorem to derive the expected posterior values of individual parameters. This is a well-established approach in the RU framework (Huber and Train, 2001; von Haefen, 2003; Scarpa and Thiene, 2005; Greene et al., 2005; Scarpa et al., 2007; Train, 2009), but it requires adjustment in our mixture models of choice behaviour. In fact, for each choice paradigm (see equations 2 and 5) we compute the conditional parameters following the method described by Scarpa and Thiene (2005). Knowing the estimated parameters under each choice paradigm and the membership probability, the expected value of parameters for each respondent given the observed sequence of choices can be approximated by simulation as follows:

$$\hat{E}[\boldsymbol{\beta}_m^n] = \frac{\frac{1}{Q}\sum_{t=1}^{Q}\boldsymbol{\beta}_m^q Pr\left(\boldsymbol{\beta}^q;\boldsymbol{\theta}^q|y^n,\pi_V\right)}{\frac{1}{Q}Pr\left(\boldsymbol{\beta}^q;\boldsymbol{\theta}^q|y^n,\pi_V\right)} \tag{12}$$

$$\hat{E}[\boldsymbol{\theta}_m^n] = \frac{\frac{1}{Q}\sum_{r=1}^{Q}\boldsymbol{\theta}_m^q Pr\left(\boldsymbol{\beta}^q;\boldsymbol{\theta}^q|y^n,\pi_V\right)}{\frac{1}{Q}Pr\left(\boldsymbol{\beta}^q;\boldsymbol{\theta}^q|y^n,\pi_V\right)}, \tag{13}$$

where q denotes the generic draw of a random coefficient, and Q the total number of draws, and

[4]Importantly, as well as the RR paradigm, this estimate is conditional on the specific set of alternative scenarios against which it is evaluated. This because, as seen in equation 3 all alternatives contribute to the computation of the observed anticipated regret.

$Pr(\boldsymbol{\beta}^q; \boldsymbol{\theta}^q | y^n, \pi_V)$ is the logit probability in equation 11 conditional on the individual set of responses. Once we know the individual posterior parameters for each choice paradigm conditional to the membership probability, it is possible to apply for each respondent an adapted version of the formula used by Scarpa and Thiene (2005) for deriving conditional individual parameters from latent class models. At this point, we only need to compute the individual class membership probability, which can be obtained as a function of the parameters retrieved in equation (12) and (13) and the set of observed sequence of T choices by respondent n, means of the Bayes formula using the 'plug-in' estimator:

$$
\begin{aligned}
\hat{\pi}_V^n &= \frac{\pi_V \prod_{t=1}^{T_n} \widehat{\Pr}_{nit}^{RU}}{\pi_V \prod_{t=1}^{T_n} \widehat{\Pr}_{nit}^{RU} + \pi_R \prod_{t=1}^{T_n} \widehat{\Pr}_{nit}^{RR}}, &(14)\\
\hat{\pi}_R^n &= 1 - \hat{\pi}_V^n, &(15)
\end{aligned}
$$

where $\widehat{\Pr}_{nit}^{RU}$ is the logit for utility maximisers given the conditional individual posterior coefficients computed in equation (12) and $\widehat{\Pr}_{nit}^{RR}$ is that for the regret minimizers, obtained using equation (13).

A series of comparisons in which the baselines are kept identical for all but a single attribute can be useful to determine the median in the sample for marginal cost of acceptance for a traffic calming strategy characterised by a given attribute change. We compute these quantities for a variety of competing alternatives schemes and discuss them in the results section. Note that given the mode of computation of RR it is important to have the same number of alternatives that were observed by respondents in the choice tasks of the actual survey of this study.

3. The Survey and the Sample

As an empirical illustration of the approach we use data from a choice experiment designed to elicit preferences for traffic calming projects amongst residents of a rural town in Northern

England, namely Sherburn-in-Elmet.

The factors used in the experiment were three traffic calming outcomes, namely (*i*) reduced noise level from road traffic (*Noise*); (*ii*) an effective speed limit (*Speed*); (*iii*) reduced length of waiting time for pedestrians to cross the road (*Wait*); and two other factors: (*iv*) the overall appearance of the Traffic Calming scheme (*Beauty*); and (*v*) the annual cost per household of the scheme in terms of increased local taxation in the form of council rates (*Cost*).

In each choice task, respondents were offered two profiles based on this attribute set plus one describing the status quo, and they were asked to choose the one that they most preferred. The choice experiment proposed eight choice tasks to each respondent using a randomised set of profiles from the full factorial.

In order to reduce the complexity of the design of the choice experiment only a limited range of attribute levels were used to construct the profiles. Three levels of annual cost (10, 20 or 30) were used to explore local households Willingness to pay (WTP) for Traffic calming scheme, along with two levels (20 or 30 mph) for Speed and three levels (60, 70 or 80dB) for *Noise*. The aesthetic component of the Traffic calming layout could be either 'basic' or 'improved', and waiting time for crossing the road could be either short (1 minute) or long (3 minutes).

Interviews were conducted in the respondents homes by trained interviewers. Respondents were asked to listen to tape recordings of traffic noise played at each of the three decibel levels. Respondents were advised that sounds levels represented noise conditions at the curb of the main road. The alternative approach of using a verbal representations of decibel levels associated with traffic noise is clearly inferior to that of exposing respondents to traffic noise recordings played at the actual noise levels specified. A further advantage of this approach is that the use of actual road noise better describes the non-linear increase in volume associated with 10 unit increases on the logarithmic decibel scale.[5] Finally, the aesthetic effects associated with the basic and improved

[5] The often used decibel is one tenth of a 'Bel'; the ladder is a seldom-used unit named in honor of Alexander Graham Bell.

design were illustrated by means of pictures of existing traffic calming schemes.

Prior to the implementation of the surveys physical measurements of noise, speed, and potential severance, expressed as average time to cross the trunk-road in the town centre, were taken so as to objectively establish the prevailing status quo conditions. A combination of focus groups and informal interviews with local people were also carried out to investigate the negative impacts of traffic at each site. These investigations were also used to inform questionnaire design. While many issues were discussed, those worth mentioning include the phrasing employed to describe Effective Speed Limits, along with the choice of payment vehicle and range of values used on the profiles.

As a means of improving prediction when modeling choice-decisions, interviewers recorded the approximate distance from each respondents dwelling to the main road (Category 1 - less than 50 yards; Category 2 - between 50 and 100 yards; Category3 - between 100 and 200 yards; and Category 4 over 200 yards). Interviewers also noted whether or not the road (and potentially any future traffic calming) was visible from the house, and whether or not road noise could be heard from inside the house. These observations were used to generate the following variables used in the definition of the membership probabilities: Dist $(1, 2, 3$ and $4)$, Visible (0-1) and Audible (0-1).

4. Results and discussion

4.1. Estimation

A total of 407 usable interviews were carried out, generating $3,256$ responses for the choice experiments. Four models specifications were estimated on this sample: two MNL models, one for each choice paradigm, labeled respectively RU-MNL and RR-MNL. Next, we estimated two LC models that simultaneously accounted for the two choice paradigms. The first latent class model (LC-MNL) only allowed for the panel nature of the model and for the two decision paradigms, but ignored preference heterogeneity within each behavioural class. In essence this model is a discrete mixture of two multinomial logits, one built according to the conventional RU and the other according to the RR. The second LC specification (LC-RPL), instead, also allows for continuous preference heterogeneity on top of the discrete mixing of the choice paradigms. This assumes all taste distributions are independently distributed normal, while the cost parameter was kept fixed in each class-paradigm. In essence this latter model is a discrete mixture of two continuous logit mixtures, one referring to the conventional RU and the other to the RR.

All models were estimated by (simulated) maximum likelihood procedures using Python Biogeme, which is a recent and more flexible development of the software Biogeme (see Bierlaire, 2003, 2009). In order to deal with the problem of local maxima, which frequently plagues latent class models, we used the CFSQP algorithm (Lawrence et al., 1997) and we run the estimations between 100 and 200 times (depending on the model) beginning iterations from random starting values and retaining those results that maximized the sample simulated log-likelihood.[6] We estimated the LC-RPL model by simulating the log-likelihood with $1,000$ quasi-random draws produced with the Latin-hypercube sampling method. The interested reader is referred to Hess et al. (2006) for further details on simulation variance of these quasi-random draws.

We first present the two model specifications that fit a given choice behaviour to the whole sample, and then move on to those specifications that consider the collection of choice sequences to be a discrete mixture of both choice behaviours, RU and RR, up to mixing probabilities that are to be estimated.

4.2. Results for single choice paradigms

Table 1 presents the results from the RU-MNL and the RR-MNL. Overall, the RR-MNL provides a better fit to the data, but only by a very small measure. In terms of fit the model are hence equivalent.

[Table 1 about here.]

[6]The procedure was coded in 'PERL' and used in combination with Python Biogeme ran under Ubuntu 10.04 LTS - the Lucid Lynx. See Boeri (2011) for a more in-depth discussion of the use of this software, which can be made available upon request to the lead author.

According to the RU-MNL, town residents would have a positive preference for a traffic calming scheme characterised by shorter waiting time for pedestrians to cross the trunk-road that splits the town, as denoted by the positive and significant coefficient for the dummy of a shorter wait. They would also value positively the aesthetically improved version of the traffic calming scheme (Beauty), as denoted by the sign and significance of the coefficient for the respective dummy variable.

On the other hand, traffic calming schemes characterised by high level of noise and those that allow a high effective speed limit would yield a lower utility for residents than those with low speed and noise levels, as denoted by the negative and significant coefficients for these variables. The coefficient associated with the scheme's cost—expressed as an increased in local rates—is negative and highly significant, as expected. All coefficient estimates have expected signs.

Comparing the individual coefficient estimates from the RU-MNL to those from the RR-MNL model we find little difference in terms of statistical significance for the estimated coefficients of the various attributes. We also note that the coefficient estimates from the RR-MNL show the same signs as those in the RU-MNL.

However, we emphasize that the interpretation of the coefficient estimates from the two models is not directly comparable, in the sense that θ measure the potential regret that is caused by a one unit change of the corresponding attribute (when comparing a considered alternative with another alternative). The word 'potential' is important here, as the actual change of regret depends on the relative performance of the alternatives in terms of their attributes: if a considered alternative has a (very) strong initial performance on the attribute, relative to a competing alternative, then a one unit change in the attribute causes only small differences in regret. In contrast, when a considered alternative has a (very) poor initial performance on the attribute, relative to a competing alternative, then a one unit change in the attribute causes large differences in regret. These context-dependent preferences—which lead to semi-compensatory behaviour—are a direct result of the convexity of the regret function presented in equation 3. Note, however, that ratios of RR-parameters, just like their RU-counterparts, can be compared in the sense that both give an indication of the relative importance of the attributes (disregarding any scale difference of attributes). Further discussion about the interpretation of RR-parameters can be found in Chorus (2010) and other papers cited in the introduction of this paper.

[Figure 1 about here.]

The coefficient for a reduced waiting time for pedestrians to cross the trunk-road is positive and significant in both models. But the meaning differs. This sign in the RR model suggests that regret increases when a non-chosen alternative characterised by a shorter waiting time is available in the choice set. This because regret is computed on the basis of the waiting time for pedestrians to cross the road *at the chosen alternative*. On the opposite side of the spectrum, the negative coefficient for the Noise level suggests that regret decreases when the level of noise level for the non-chosen alternative is higher and, as a result, this alternative is less attractive when compared to the chosen alternative with lower noise level.

As suggested by an anonymous reviewer, to help the reader visualise the differences between β and θ we include Figure 1 in which we plot the ratios between each attribute coefficient and the tax coefficient estimated from the MNL model. On the horizontal axis we plot ratios from RU estimates and the ratios based on RR choice paradigm are on the vertical axis. This allows for a visual comparison across models estimates. The figure shows that *Beauty* and *Wait* are estimated as relatively more important for RR, while *Speed* and *Noise* for RU.

Finally, we notice that in both RU-MNL and RR-MNL the coefficient for the status-quo specific constant, which refers to the current situation, is positive and highly significant. This suggests that respondents tend to prefer the status quo and/or they are reluctant to implement any of the proposed traffic calming schemes. This status-quo bias is often observed in similar empirical studies (Scarpa et al., 2005; Boxall et al., 2009; Marsh et al., 2011; Hartman et al., 1991) and has been the subject of several theoretical investigations (Samuelson and Zeckhauser, 1988; Hartman et al., 1991; Michael, 2004). In essence the two models do not display major differences in terms of their qualitative description of preferences for attributes.

4.3. Results for mixture of choice paradigms

Estimates for the two models with mixtures for both the LC-MNL and LC-RPL models are presented in Table 2. In terms of model fit, as demonstrated by the relative values of the information criteria, the LC-MNL model outperforms the MNL models and in turn the LC-RPL improves the fit to the data even further, as one would expect. This corroborates the hypothesis that taste heterogeneity as well as paradigm heterogeneity co-exist in our sample of choices.

[Table 2 about here.]

Some of the coefficient estimates signs for the LC-MNL model are discordant across behavioural classes. For example, *Noise* and *Speed* and *SQ* have different signs across classes. *Beauty* and *Wait*, instead, are positive in both classes, while *Tax* is negative in both classes. Respondents members of the RR-class emerge as being inclined to prefer the current situation, while respondents in the RU-class do not. This apparent association between regret minimization behaviour and an inclination to choose the status quo option is in line with previous empirical results obtained in the field of (consumer) psychology (Ritov and Baron, 1995; Ordóñez et al., 1999; Zeelenberg and Pieters, 2007).

Another interesting difference between the two classes is that the coefficient for the effective speed limit is negative for the class characterised by utility maximization and positive but statistically insignificant for the class focused on regret minimization. This suggests that for respondents who choose by minimizing their regret speed is not as important as for those who choose maximising their utility.

Overall the LC-MNL results corroborates the existence of an articulated set of differences, which remain unobserved in the results of the MNL models that imposed common behavioural assumptions across all respondents in the sample.

The LC-RPL model, which incorporates heterogeneity in preference within each class, produces two effects worth noting. The first is a sign reversal in the mean value of the coefficient for speed in the RU class, which is negative when the coefficient is not random, and shows positive mean and a large variance in the LC-RPL. A large variance is also found in the RR class. Taken jointly these results provide strong evidence of great variability in the values of the utility weights assigned to speed across respondents. In both the RU and RR classes there is strong polarization around zero, in the sense that the size of the spread parameter relative to that of the mean implies a near-equal split between positive and negative coefficient values in the population. Since randomness has been modelled by imposing each random coefficient to take a normal distribution it is immediate to compute the implied fractions of respondents with negative weighted coefficients for both classes. For the RR class this is $\Phi(\hat{\xi} = 0.030, \hat{\omega} = 0.102) = 0.384$, while for the RU class this is $\Phi(\hat{\mu} = 0.011, \hat{\sigma} = 0.157) = 0.472$. The complements of 0.616 for RR and of 0.528 for RU refer to the fractions with positive values. These polarised views on effective speed limits are not uncommon. It had previously emerged as such in the focus groups conducted in the phase of the survey instrument design. While most residents welcome effective speed reduction on the grounds of safety, a good fraction of them (mostly made up by drivers) see traffic calming schemes—and especially speed restriction effects—as a nuisance.

We note that the apparent anomaly of a positive coefficient on noise—which emerged in the RU class for the LC-MNL—disappears in the LC-RPL, in which both RU and RR classes have the expected negative mean, with relatively low variance estimate.

All random coefficients for the RU-class and all but *Beauty* for the RR-class have significant estimates for standard deviations, which imply a significant presence of heterogeneity across individuals. In conclusion, preference heterogeneity appears to be an important factor in both choice behaviour classes. The specification that incorporates both sources of heterogeneity in the form of choice behaviour, as well as taste variation, fits the data significantly better than the specification that allows only for heterogeneity in choice behaviour. While this is expected, both LC models provide the analyst with a much richer set of behavioural information, for the interpretation and validation of which we now turn our attention to the role of paradigm determinants.

To illustrate, in Figure 2 we plot the values obtained from the RU class on the horizontal axis and the values obtained from RR class on the vertical. Figure 2(a) plots values from the LC-MNL model, while Figure 2(b) contains values from the LC-RPL model with the standard errors of the distributions around the mean values. Note how the latter shows a pattern similar to that of the 2 MNL estimates.

[Figure 2 about here.]

4.4. Determinants of choice paradigms

The estimates of the coefficients determining class membership probabilities afford the analyst an understanding of what systematically correlates with each of the two choice paradigms. The membership probability for the class with RU choice behaviour are as in equation (7). The average of the individual-specific membership probabilities gives a 57.3 percent probability of belonging to the RU class according to the LC-MNL model and 56.1 percent according to the LC-RPL model. So, the RU paradigm dominates in both models, but not by far.

The coefficient estimates for selected combinations of socio-economic determinants of class membership are presented in table 3 for both LC models, and placed side by side to ease comparison. These refer to determinants of class membership probabilities for the RU-class using as a baseline a value of zero (necessary for identification) for the membership to the RR-class.

The negative and significant ASC indicates a marginal propensity for the baseline group (which includes respondents who do not drive, can neither see nor hear the road and have no school age Kids) to belong to the RR class. All other coefficients have positive signs and hence indicate a propensity to belong to the RU class. Three of these (*drivers-to-work, audible* and *school aged kids*) are statistically significant. In the LC-RPL mode, which accounts for within class unobserved preference variation across respondents, the membership coefficient for the constant associated with the baseline group, *driver-work*, and *audible* are higher in both value and significance.

[Table 3 about here.]

In the three blocks of the lower part of table 3 we report the sample average of the individual membership probabilities and the membership probability computed for each combination of socio-economic determinants. These are separated in three blocks of eight each. Block A reports the case for respondents who mostly drive for work, block B reports the case of respondents who mostly drive for hobby, while block C reports the predicted probabilities of membership for those who do not drive regularly.

We notice that having to drive regularly for work or hobby—values in rows $A1$ and $B1$—increases the probability of membership to the RU class. More so for those having to drive for work (nearly 20% more likely to be in the RU class). The second largest impact on RU membership is predicted to be that of having school-age kids or living in a location from which the traffic on the trunk road is audible, as can be seen comparing the pairs of values in $A1, A6$ and $B1, B6$ and $C1, C6$ and those in the pairs $A1, A8$ and $B1, B8$ and $C1, C8$.

In general, residents who drive, have children to drive to school and for whom the main road is visible or audible have high probability of membership to the RU-class. On the other hand, respondents who do not drive or drive only for leisure, have no school-age children to drive to school or who cannot either see or hear the main road from the place of residence are more likely to be assigned to the RR-class. This suggests that respondents who are familiar with the attributes underlying the choice context tend to adopt choice behaviour more in keeping with RU maximization, while respondents who are less familiar with it are more likely to adopt choice behaviour consistent with RR minimization. This finding appears to be in line with previous work in consumer psychology, where it has been argued that regret minimization is a particularly important determinant of decision making when decision-makers find it difficult to make the right decision (Zeelenberg and Pieters, 2007) perhaps for lack of experience. In our case results suggests that the more familiar a respondent is with the road (either as a driver or by proximity to it), the more he/she will choose maximising his/her utility without considering the performances of the non-chosen options. Other respondents are more inclined to choose options by minimising their regret because they may be afraid that non-chosen traffic calming scheme may perform better than the chosen one, on the basis of one or more attributes. An alternative interpretation is that those who can avoid rush-hour traffic and use the trunk road less frequently—such as those who drive mainly for leisure and those who do not drive children to school—are more likely to be attracted by traffic calming schemes characterised by 'in-between' performance of the attributes compared to other schemes that may have a poor performance on some attributes and a good performance on other attributes.

We generally observe substantive convergence across the two versions of the LC model in the direction and intensity of the effects of determinants of choice behaviour. Some exceptions are worth discussing. For example, those who drive mostly for hobby seem to be affected differently by whether or not they have school age kids and the road is visible from their homes. Those with kids and visibility are predicted as RR minimizers by the LC-RPL, but not so by the LC-MNL. A similar effect is noted for those with school age kids and those who do not drive who have a higher probability to be classified as RR minimizer by the LC-RPL model. In as much as one finds it plausible that respondents with school age kids are more inclined to make choices using regret minimization, which we find quite plausible, this result corroborates the validity of the best performing model, the LC-RPL.

5. Welfare impacts of selected calming schemes

Estimating the welfare effects of different traffic calming schemes was one of the most important and challenging objective of this study. Deriving welfare measure from a hybrid model that includes two choice paradigms as well as heterogeneity in preferences, is not straightforward. In this section we explain how we estimate the maximum cost that our sample of residents are willing to pay for a traffic calming policy when compared with alternative schemes. Assuming the scheme is to be voted in via a local referendum poll, the quantity of interest is the amount that at least fifty percent of the residents would be willing to pay. The need of predefined alternative traffic calming schemes is necessary for welfare estimate derivation in the RR context. This because regret is a relative function of choice set composition. In our case the alternative traffic calming schemes on offer are compared to the current traffic situation (SQ), defined as 70db of noise, 40 Miles/h of speed limit and no improvements in waiting time for pedestrians to cross the road (*Wait*) nor in the overall appearance of the Traffic Calming scheme (*Beauty*), which is currently missing. The candidate alternatives are various traffic calming schemes. These include, respectively, an improvement in Wait (3a) or Beauty (2a) and in both characteristics (1a) leaving the level of noise and the speed limit unchanged. We then compare the SQ to an improvement in Wait (3b) or Beauty (2b) and in both characteristics (1b) considering in all the alternatives an additional reduction of noise levels at the curb from 70db to 60db. Results are shown in Table 4.

[Table 4 about here.]

For example, the third row shows that the aesthetics of the Traffic Calming scheme are valued by respondents. Scheme 3a leaves all attributes unchanged and only adds *Beauty* to the status quo. When contrasted with schemes 1a, 2a and the status quo, scheme 3a is associated with a maximum majority value of about 3.2 pounds per respondent. At any higher amount the scheme 3a would fall below majority support.

Candidate scheme 1a—in the second row of the Table 4—has a maximum majority value of 0.6 pounds per respondent higher than scheme 3a because it also offers a reduction in waiting time for pedestrians to cross the road, but it is evaluated in a consideration set that includes schemes 2a, 3a and the status quo. Finally, candidate scheme 2a isolate the effects of reduced waiting time and leaves all attributes unchanged. When evaluated in a consideration set including 1a, 3a and the status quo it is associated with a maximum majority value of 1.1 pounds per respondent. The examples above illustrate well the fact that the marginal effects in terms of maximum majority value depend on the compositions of the consideration sets. So, when regret is involved, welfare estimates are clearly dependent on irrelevant alternatives.

Moving our attention to the candidate schemes that reduce the level of noise from the road from 70db to 60db (rows 4,5 and 6 of Table 4), we note how these candidate schemes would be voted in even at a considerably higher maximum majority value (about 10 pound per respondent more than the first set of alternative schemes). The level of noise of the truck road seems to be the main cause of regret and utility for our sample of respondents.

6. Conclusions

Our empirical investigation of two probabilistic decision processes into separate and integrated models suggests that a substantial share of our sample of town residents expressed a choice pattern of traffic calming schemes that is better explained by RR minimization than RU maximization, although the majority provides choice patterns consistent with the latter. In terms of choice modelling, we showed how to accommodate this fraction using a discrete mixture of choice behaviours in line with other published analysis of the same type. This literature tries to accommodate various probabilistic decision processes via the identification of additional choice behaviours that might accompany the standard RU assumption in real data. These can either take the form of attribute processing (e.g. Scarpa et al., 2009; Hensher and Greene, 2010) or selective treatments of cost information (Campbell et al., 2012) or the form of other postulated choice behaviour paradigms, such as lexicography, elimination by aspect, etc. (Hess et al., 2012). Juxtaposed to this mixture of RU and RR choice behaviours we also accounted for the well-known issue of unobserved preference heterogeneity within each choice behaviour class as described in Bujosa et al. (2010); Hess et al. (2012) and Hensher et al. (2012a).

Our results align with what has been found in studies applying similar choice modeling techniques, as well as with related empirical work from the field of (consumer) psychology. These modifications produce a better fit to the data, suggesting that the inclusion of these elements improves the realism of the mathematical models used to explain observed choice. A novel finding is represented by conditioning class behaviour membership on socio-economic co-variates, which are often elusive in these empirical contexts. This helps explaining the drivers of choice behaviour.

In line with evidence reported in the literature from the field of consumer psychology, we find evidence corroborating the hypothesis that lack of familiarity with the choice situation (in this case, the traffic situation) triggers regret minimization behaviour as opposed to utility maximization behaviour.

In addition, we focused on exploring the effects on the resulting specification on benefit estimates. This because estimation of WTP is the purpose of many applied studies, especially in public economics in the context of local public good provision. Because of the dependency of RR measures on the entire composition of the choice set, benefit estimates in the RR framework are not amenable to close-form derivations. We hence computed the maximum monetary amount residents are willing to spend for the proposed traffic calming scheme which is still sufficiently low to be afforded by the majority of residents at the local council level. These benefit estimates are applicable to RU and RR probabilities alike and therefore to their mixtures. Benefit estimates are highest for the proposed reduction of noise and larger for the proposed aesthetic improvements than for the proposed reduction in waiting times for crossing the trunk road separating the two parts of town. Importantly, because of the presence of regret they are dependent also on the set of alternatives against which they are compared.

We believe this empirical study moves the frontier of choice modeling towards a more realistic understanding of both observed choice and how to use formal models of choice for benefit estimation. The provision and funding of local public goods is often cause of heated debates in public policy. We are hopeful that improvements in the modeling of the sources of potential economic benefits for the collective can better inform this important policy arena.

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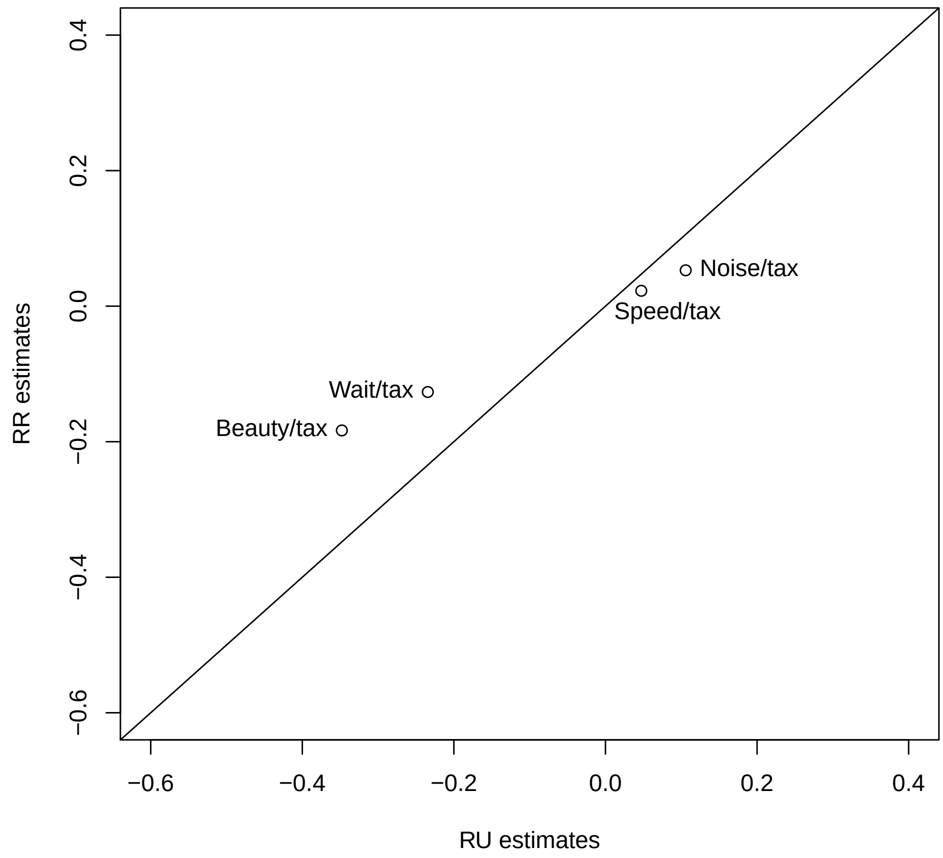
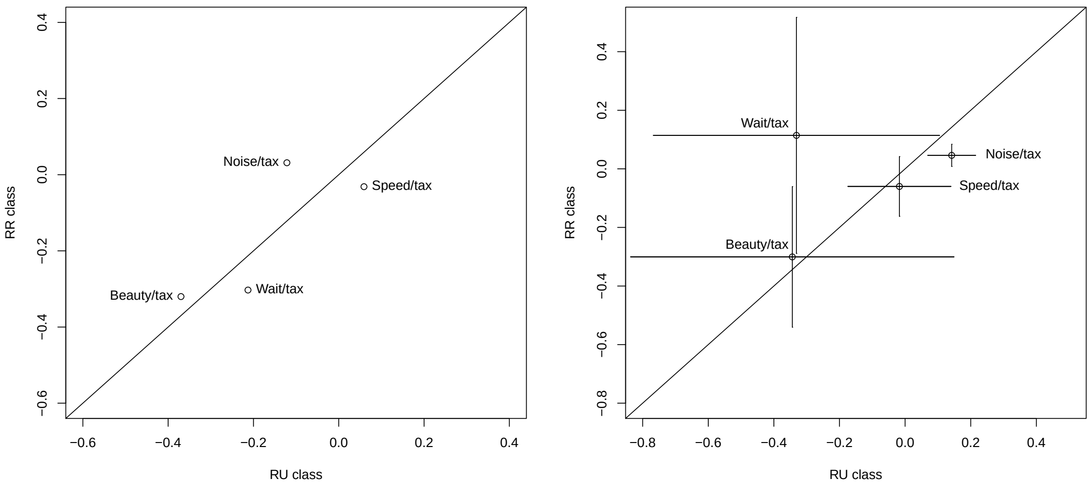
List of Figures

Figure 1: RU and RR in the MNL models.



(a) Ratios of parameters in the two MNL model's specifications

Figure 2: RU and RR in the 2 LC models' specifications.



(a) Ratios of parameters in the two classes specified in the LC-MNL model

(b) Ratios of parameters in the two classes specified in the LC-RPL model

List of Tables

Table 1: Comparing RU and RR in MNL models; $3,256$ observations

	RU			**RR**	
	Coeff. Est.	*|t-rat.|*		*Coeff. Est.*	*|t-rat.|*
β_{Noise}	-0.056	17.26	θ_{Noise}	-0.028	16.95
β_{Speed}	-0.025	4.68	θ_{Speed}	-0.012	4.59
β_{Beauty}	0.184	3.44	θ_{Beauty}	0.097	3.60
β_{Wait}	0.124	2.35	θ_{Wait}	0.067	2.52
β_{Tax}	-0.529	15.19	θ_{Tax}	-0.262	15.64
β_{Sq}	0.351	3.29	θ_{Sq}	0.421	3.99
ρ^2	0.112		ρ^2	0.113	
$\mathcal{L}(\hat{\beta})$	$-4,002.139$		$\mathcal{L}(\hat{\beta})$	$-4,000.909$	
BIC	$8,052.808$		BIC	$8,050.348$	
AIC	$8,016.278$		AIC	$8,013.819$	
3AIC	$8,022.278$		3AIC	$8,019.819$	
crAIC	$8,016.485$		crAIC	$8,014.025$	

Table 2: Latent class RU and RR models with and without taste heterogeneity

$N = 3,256$		LC-MNL			LC-RPL	
		Coeff. Est.	$\|t\text{-rat.}\|$		*Coeff. Est.*	$\|t\text{-rat.}\|$
class RU	β_{Noise}	0.072	17.72	μ_{Noise}	−0.090	11.41
				σ_{Noise}	0.073	8.99
	β_{Speed}	−0.035	5.43	μ_{Speed}	0.011	0.75
				σ_{Speed}	0.157	10.89
	β_{Beauty}	0.219	3.46	μ_{Beauty}	0.218	2.54
				σ_{Beauty}	0.493	3.43
	β_{Wait}	0.126	2.05	μ_{Wait}	0.210	2.55
				σ_{Wait}	0.436	2.88
	β_{Tax}	−0.592	13.99	β_{Tax}	−0.634	10.31
	β_{Sq}	−1.620	10.54	β_{Sq}	−3.030	10.56
class RR	θ_{Noise}	−0.011	2.17	ξ_{Noise}	−0.023	2.32
				ω_{Noise}	0.038	3.11
	θ_{Speed}	0.011	1.24	ξ_{Speed}	0.030	1.64
				ω_{Speed}	0.102	5.88
	θ_{Beauty}	0.112	1.34	ξ_{Beauty}	0.150	1.41
				ω_{Beauty}	0.240	1.19
	θ_{Wait}	0.106	1.29	ξ_{Wait}	−0.057	0.51
				ω_{Wait}	0.403	2.54
	θ_{Tax}	−0.350	6.01	θ_{Tax}	−0.499	5.21
	θ_{Sq}	1.740	5.50	θ_{Sq}	2.340	4.44
	ρ^2	0.314		ρ^2	0.362	
	$\mathcal{L}(\hat{\beta})$	−3,079.106		$\mathcal{L}(\hat{\beta})$	−2,853.670	
	BIC	6,497.919		BIC	6,111.753	
	AIC	6,242.212		AIC	5,807.340	
	3AIC	6,284.212		3AIC	5,857.340	
	crAIC	6,291.692		crAIC	5,890.112	

Table 3: Membership models for RU class in mixture models and membership probabilities

	LC-MNL		**LC-RPL**	
	Coeff. Est.	$\|t\text{-}rat.\|$	*Coeff. Est.*	$\|t\text{-}rat.\|$
ASC*	−1.100	4.11	−1.430	4.27
driver-work	0.959	3.08	1.130	3.25
driver-hobby	0.413	1.68	0.318	1.15
visible	0.107	0.40	0.153	0.51
audible	0.961	3.28	1.290	3.81
school age kids	0.987	3.29	0.958	2.83
	Probabilities in percentage			
	$\widehat{Pr}(RU)$	$\widehat{Pr}(RR)$	$\widehat{Pr}(RU)$	$\widehat{Pr}(RR)$
Average of individual-specific membership probab.	57.30	42.70	56.01	43.99
$A1$.driver-work	46.50	53.50	42.56	57.44
$A2$.driver-work + visible	49.20	50.80	46.33	53.67
$A3$.driver-work + visible + audible	71.60	28.40	75.82	24.18
$A4$.driver-work + visible + audible + school age kids	87.10	12.90	89.10	10.90
$A5$.driver-work + audible + school age kids	85.90	14.10	87.52	12.48
$A6$.driver-work + school age kids	70.00	30.00	65.88	34.12
$A7$.driver-work + visible + school age kids	72.20	27.80	69.23	30.77
$A8$.driver-work + audible	69.40	30.60	72.91	27.09
$B1$.driver-hobby	33.50	66.50	24.75	75.25
$B2$.driver-hobby + visible	35.90	64.10	27.71	72.29
$B3$.driver-hobby + visible + audible	59.40	40.60	58.20	41.80
$B4$.driver-hobby + visible + audible + school age kids	79.70	20.30	78.40	21.60
$B5$.driver-hobby + audible + school age kids	77.90	22.10	75.69	24.31
$B6$.driver-hobby + school age kids	57.40	42.60	46.16	53.84
$B7$.driver-hobby + visible + school age kids	60.00	40.00	49.98	50.02
$B8$.driver-hobby + audible	56.80	43.20	54.44	45.56
$C1$.ASC*	24.97	75.03	19.31	80.69
$C2$.not driver + visible	27.03	72.97	21.81	78.19
$C3$.not driver + visible + audible	49.20	50.80	50.32	49.68
$C4$.not driver + visible + audible + school age kids	72.21	27.79	72.53	27.47
$C5$.not driver + audible + school age kids	70.01	29.99	69.38	30.62
$C6$.not driver + school age kids	47.18	52.82	38.41	61.59
$C7$.not driver + visible + school age kids	49.85	50.15	42.09	57.91
$C8$.not driver + audible	46.53	53.47	46.51	53.49

* The baseline group is composed by respondents who do not drive and can neither see nor hear the road and have no school age Kids.

Table 4: Maximum costs in GBP per year to vote in candidate traffic calming schemes

Candidate scheme	*noise*	*speed*	*beauty*	*wait*	*Other schemes in the set*	*Cost*
$1a$	70	40	1	1	$2a, 3a, SQ$	3.8
$2a$	70	40	0	1	$1a, 3a, SQ$	1.1
$3a$	70	40	1	0	$1a, 2a, SQ$	3.2
$1b$	60	40	1	1	$2a, 3a, SQ$	13.0
$2b$	60	40	0	1	$1a, 3a, SQ$	10.5
$3b$	60	40	1	0	$1a, 2a, SQ$	11.8
SQ *values*	70	40	0	0		