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A comparison of regret-based and utility-based discrete choice modelling – an empirical illustration with hospital bed choice

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ABSTRACT
There is some concern that the unobserved preference heterogeneity in random utility maximization theory-based discrete choice experiment modelling is an important source of error variability. The randomness in utility is often interpreted as interpersonal preference heterogeneity but it can also be intrapersonal random variation in preferences. We compare utility maximization and regret minimization-based choice models' sensitivity to individual heterogeneity, examine differences between two consecrated models and validate with empirical illustrations. We use frequency of category (public, semi-private, and private) of bed chosen from Swiss cross-sectional datasets (2007–2012) to compare two approaches – utility maximization and regret minimization by applying multinomial logit (MNL) models in regard to the variances in utility (regret) function, goodness-of-fit and predicted marginal effects (pseudo-elasticity) of additional payment. We find parameters with the same sign and estimates with almost same order of magnitude in both the approaches. The statistical significance of attribute effects is consistent in all variants of utility -based MNL models while effects of different attributes are significant only in heteroskedastic extreme value (HEV) variant of regret-based MNL models. This empirical illustration suggests that HEV variant of regret-based models perform better in capturing attribute effects in choice behaviour.

KEYWORDS
Behavioural paradigm; choice modelling; hospital bed choice; pseudo-elasticity and random regret

JEL CLASSIFICATION
C25; D12

I. Introduction

The discrete choice experiment (DCE) approach combines random utility theory (RUT), consumer theory, experimental design theory, and econometric analysis (Bliemer and Rose 2006; Hensher, Rose, and Greene 2005; Lancsar and Louviere 2008; Louviere, Hensher, and Swait 2000; Ryan, Gerard, and Amaya-Amaya 2008). The debate in advancing DCE practices focuses on the recurring themes of 'experimental design', 'estimation procedures', and 'validity' (Louviere and Lancsar 2009; Ryan and Gerard 2003). Wansbeek, Meijer, and Wedel (2001) have argued for individual heterogeneity at the micro level, while Louviere and Lancsar (2009) recommend the inclusion of interaction terms in the design and analysis stages of DCE in addition to recognizing heterogeneity as one of the many potential sources of choice variability.

A systematic review study by De Bekker-Grob, Ryan, and Gerard (2012) reports an increasing use of DCEs in a broader range of health systems – for appraising patient experience factors; valuing health outcomes; making trade-offs between health outcomes and patient experience factors; estimating utility weights within the quality adjusted life year framework; understanding labour-market choices; developing priority setting frameworks; and examining clinicians' choices for case management preferences. This review has also found a shift towards statistically more efficient designs and flexible econometric models.

The DCE modelling applications are based on linear-additive random utility maximization (RUM) theory (Manski 1977; Thurstone 1927) and the derived logit model (Ben-Akiva and Lerman 1985; McFadden 1974; Train 2009). RUT is based on the premise that some components of preferences are unobservable to the researcher and therefore treated as random (Manski 1977; McFadden 1974; Thurstone 1927). Random utility choice models are robust to violations of compensatory decision-making as well as to violations of strictly additive (i.e. 'main effects only') utility functions (Louviere, Hensher, and Swait 2000). The

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success of RUM models is premised on the intrinsic elegance of RUM theory, its firm foundation on (welfare) economic axioms (Small and Rosen 1981), empirical performance due to its strong econometric foundations, and its formal tractability.

Application of the RUT-based model demands decomposition of utility into a systematic or explainable component and a random or unexplainable component. The random component is generally thought to be capturing all unobserved heterogeneity. This random component is also interpreted as the researcher's inability to capture respondent preferences accurately (Louviere, Hensher, and Swait 2000). Ben-Akiva and Lerman (1985) have argued that the random component captures errors made by the individual in forming and revealing their preferences based on their utility maximization process. Furthermore, McFadden (1997) suggests that the randomness in utility, usually interpreted as interpersonal preference heterogeneity, could equally well be interpreted as intrapersonal randomness in preferences. Thus, unobserved preference heterogeneity, as an important source of error variability, limits the application of DCEs (Louviere 2004a; Louviere 2004b). Hence, it is being argued that evidence suggests that the choice paradigm based on RUM lacks behavioural realism (Hess, Stathopoulos, and Daly 2012).

The developments within the RUM-based models, which aim to overcome the limitations by introducing the assumption (1) of fully compensatory decision-making (Arentze and Timmermans 2007; Swait 2001) and (2) insensitivity to choice set composition (Kivetz, Netzer, and Srinivasan 2004; Zhang et al. 2004), are without exception less parsimonious and less tractable (Thiene, Boeri, and Chorus 2012). The assumptions subscribing economic axiom of continuity can be empirically validated with richer datasets, having an array of situational variables and/or individual preferences. This study, a straightforward approach, is not designed to adopt a view based on certain simplifying heuristics.

The essence of regret theory is that individuals compare their actual situations with ones that would have occurred had they made a different choice. The choice models based on random regret minimization (RRM) are 'semi-compensatory'[1] and are independent from the irrelevant alternatives (IIA)[2] property. The IIA property is characteristic of RUM models, even when errors are assumed to be identically and independently distributed (i.i.d).[3]

Further, the ability of RRMs to display semi-compensatory decision-making and choice-set effects, like the compromise[4] effect, does not come at the cost of added parameters as with other models that aim to capture these behavioural phenomena. The behavioural premise of the RRM model is that the decision-makers aim to avoid the situation where a non-chosen alternative performs better than a chosen one in terms of one or more of its attributes and such premise adds parsimoniousness to RRM-based choice modelling (Chorus 2010; Chorus and De Jong 2011; Chorus and Rose 2011). The attribute-based measure of benefit is based on the assumptions that the value an individual assigns while consuming (choosing) health services depends upon the levels of the attributes.

This study is inspired by Boeri et al. (2013) who recommend that the models based on regret minimization for modelling the behavioural influences are more precise than simply using utility theory-based models that assume the utility maximization framework being driver of choices in all situations.

In this article, we compare the utility maximization and the regret minimization models in choice experiments. This article is structured as follows: the next section presents a concise

[1]The RRM model predicts that the level of improvement of one attribute that is needed to compensate for the deterioration of another attribute depends on how the alternative performs, relative to the other alternatives, in terms of both attributes. This implies that when some attribute (x), which has deteriorated, is equally important as another one (y), which has improved, (i.e. the parameter estimates are the same), and the magnitude of the deterioration equals the magnitude of the improvement, the improvement in y does not necessarily compensate for deterioration in x.

[2]The IIA property is described as the ratio of choice probabilities of any two alternatives that is not affected by having a new alternative entering into the choice set, nor by changing the performance of another alternative in the choice set. By contrast, RRM models postulate that any ratio of choice probabilities can be, and is even is likely to be, affected by the presence of new alternatives or by changes in the performance of any third alternative.

[3]This means that errors assigned to different alternatives are uncorrelated, and are drawn from the same distribution (with the same variance). This variance is usually fixed to $\pi 2/6$, which indirectly implies a normalization of systematic utility.

[4]The RRM model predicts that having a (very) poor performance on one attribute causes much regret, while having a (very) strong performance on another attribute does not necessarily compensate for this (very) poor performance. As a result, it is more efficient (in terms of avoiding regret) to 'move to the centre' of the choice set: An alternative that fails to have a really strong performance on any of the attributes (relative to the other alternatives) still only generates modest levels of regret as long as it does not have a particularly poor performance in any of the attributes.

theoretical summary on utility and regret-based approaches of choice models, Section III captures description of data and empirical implementation of these models. Results and discussions are presented separately in Section IV and in Section V respectively. Section VI concludes with comments on performance of these models on our data and provides direction of applicability of such models in health system.

II. Utility and regret-based approaches of choice models

The RUT-based (Manski 1977; Thurstone 1927) multinomial logit (MNL) model is based on the assumption that, when choosing, a respondent maximizes his/her utility function:

$$U_{ni} = V_{ni} + \epsilon_{ni}, \tag{1}$$

where U_{ni} is the maximized utility function of nth respondent on choosing i alternative. V is the observed component and ϵ is the unobserved component of the utility.[5] The observed utility function (linear), $V_{ni} = \beta' X_{ni}$, X is a vector of m attributes reflecting alternative i, and β is a vector of the m parameter to be estimated. β_m captures the slope of the utility function for the m attribute. A positive and statistically significant β_m indicates a positive contribution of the attribute to the utility of the individual. Conversely, a negative and significant β_m suggests that the respondent dislikes the alternatives by higher levels of the corresponding attribute m. Thus, the probability of individual n choosing alternative i over another alternative j is expressed as (McFadden 1974):

$$P_n(i) = \frac{\exp(V_{in})}{\sum_{j=1}^{J} \exp(V_{jn})}, \ J = \text{a choice set}. \tag{2}$$

The RRM approach posits that when choosing from a set of alternatives, decision-makers aim to minimize anticipated regret:

$$\varphi_{ni} = R(\theta, X_{ni}) + \omega_{ni}, \tag{3}$$

where φ_{ni} represents the regret function minimized by respondent n when alternative i is chosen, R is the observed part of the regret, θ is a vector of the parameters to be estimated and ω (i.i.d.) is the unobserved part of the regret function.

Thus, the observed part of the regret function (Chorus 2010) is expressed as

$$R_{in} = \sum_{j \neq i} \sum_{m} \ln\left[1 + \exp\left\{\theta_m \left(x_{jnm} - x_{inm}\right)\right\}\right], \tag{4}$$

Here, the observed part of the regret is defined as the sum of all the regrets associated with the attributes m between the choice sets of i and j. θ_m captures the slope of the regret function for attribute m.

The estimated coefficients reflect the potential contribution of an attribute to the regret associated with that alternative. A positive coefficient for an attribute suggests that regret increases when the difference in that attribute between a chosen and a non-chosen alternative increases. A negative coefficient for an attribute implies that regret increases when a considered alternative is compared to another alternative with a decreasing value for that attribute. Hence, the extent of the upper bound by which a unit increases in the relative performance of an attribute influences the level of regret that is associated with a comparison of another alternative measured with θ_m.

With the assumption that minimization of the random regret is mathematically equivalent to maximization of the negative of the random regret (the negative of the unobserved part of the random regret, ω_{in}), the probability of choice for individual n is expressed as (Chorus 2010):

$$P_{in} = \frac{\exp(-R_{in})}{\sum_j e(-R_{jn})} \tag{5}$$

Equations (2) and (5) are both logit-type closed-form expressions and result in choice probabilities that are equally parsimonious (Boeri et al. 2013).

The parameters are estimated with the maximization of the log-likelihood function. The random utility-based

[5]The assumption is that error terms are i.i.d. extreme values (Train 2009; Ben-Akiva and Lerman 1985). The mean of the extreme values' distribution is not zero, however; the difference between two error terms that have the same mean is zero. The difference between two extreme value distributions is the logistic distribution. Therefore, using the extreme value distribution for the errors, which implies the logistic distribution for the error differences, is almost the same as assuming that the errors are independently normal. Train (2009) has shown that an extreme value distribution gives slightly fatter tails than a normal value distribution, which means that it allows for slightly more aberrant behaviour than the normal value distribution.

choice model acknowledges that respondents use a fully compensatory[6] behaviour, while the random regret-based choice model implies semi-compensatory[7] decision-making.

It has been argued that much of the heterogeneity in attribute weights can be accounted for by a scale effect varying across individuals (Fiebig et al. 2010; Louviere and Eagle 2006; Louviere and Lancsar 2009; Louviere et al. 2002; Louviere et al. 2008; Meyer and Louviere 2007). The heteroskedastic extreme value (HEV) variant of the MNL model with its freedom from the IIA assumption allows for disturbances in the utility functions (differential cross elasticities amongst alternatives). The derivatives and elasticities of the probabilities differ across all alternatives and attributes. The heteroskedasticity alone interrupts IIA assumption.

The general form of the (HEV) variant of MNL derives from a random utility model with heteroskedasticity across individuals, rather than across choices with an error term as a Gumbel (independent extreme value) distribution (McFadden 1974). The variance ϵ_{ni} (Equation (1)) is equal to ${\pi^2}/{6}$ but variance in HEV allows separate variance for each ϵ_{ni} (Bhat 1995). We compare ratios of variances and so, one of the θ's is normalized to 1.

$$P_n(i) = \frac{\exp(\beta_i V_{in})}{\sum_{j=1}^{J} \exp\left(\beta_j V_{jn}\right)}, \beta_i \tag{6}$$

β_i is the individual specific parameter vector.

III. Application of models: empirical implementation

Empirical implementation

To examine the difference in compensatory behaviour in decision-making by the individual, we estimated both the regret minimization-based and utility-based MNL models.

We have used the cross-sectional datasets of hospitalization (sourced from *Sekretariat der Expertengruppe Gesundheitsstatistik*, the Swiss Federal Statistical Office [FSO]) for six years (2007–2012). Respondents with only compulsory health insurance with seven selected types of diagnosis – namely (1) abortion; (2) angina, (3) hypertension, (4) joint stiffness and pain, (5) osteoarthritis, (6) thrombophlebitis, and (7) varicose veins – are included in this study.

Datasets have been collected from the Swiss FSO, Espace de l'Europe 10, 2010 Neuchâtel (http://www.bfs.admin.ch/bfs/portal/de/index/themen/14/03/01/key/01.html). The administrative datasets made available for this study contained information on 8.5 million patients (approx.1.5 million for each year) for the 6-year (2007–2012) period. For this study, we extracted 7.6 million records (approx.1.3 million for each year) representing the population covered only with compulsory health insurance (i.e. we excluded the population with additional coverage). The final sample comprised 776,348 anonymized cases representing the population with one (or more) of the seven diagnoses and having only compulsory health insurance.

The patient choices were for the three categories of hospital bed (public with four beds, semi-private, and private).[8] Although the datasets covered 6 years but tracking individuals within the available datasets was not possible; so, we used the frequency of category of the bed chosen, the anonymized datasets were clustered by diagnosis, gender, age group, comorbidity, and year. Thus, this study covers 155 groups. Table 1 provides the descriptive characteristics of the grouped data, used in this study.

Our dataset was multinomial, level balanced, and orthogonal with a minimal D_b-error criterion (Ferrini and Scarpa 2007).[9] The choice of hospital bed by the Swiss population with a selected diagnosis is the

[6]Fully compensatory behaviour suggests that individuals, when trading off attributes defining an alternative, follow a decision rule that allows a positive evaluation of an attribute to compensate for a negative evaluation of another attribute.

[7]Semi-compensatory behaviour assumes that individuals adopt a decision rule that does not allow for a bad performance of an alternative with respect to an attribute to be directly compensated for by the good performance of another attribute. This means that improving an alternative in terms of an attribute on which it already performs well relative to other alternatives generates only small decreases in regret, whereas a corresponding deterioration of the performance of another equally important attribute on which the alternative has a poor performance relative to other alternatives may generate substantial increases in regret.

[8]The bed categories in Swiss hospitals for elective admissions are: (1) a public bed in a shared room with four beds, (2) a semi-private shared room with two beds under the direct care of a senior clinician, and (3) a private room (single occupancy) under the care of the head clinician. Swiss nationals with only compulsory health insurance are only entitled to a public bed. The choice of a higher category hospital bed requires additional payment or supplementary health insurance cover.

[9]The criterion refers to a Bayesian design that allows the inclusion of the uncertainty of subjective a priori information (β) on the values of a certain population b. More precisely, minimization applies to the expected value of the D-criterion with respect to its distribution over β or $\pi(\beta)$ (in other words, Db).

Table 1. Data characteristics.

	N = 776,348
Diagnosis (%)	
Abortion	11.29
Angina	10.71
Hypertension	1.81
Joint stiffness and pain	1.64
Osteoarthritis	58.08
Thrombophlebitis	0.32
Varicose veins	16.16
Gender (%)	
Male	36.94
Female	63.06
Age group (%)	
19–39 years	13.87
40–59 years	17.45
60–74 years	37.21
≥75 years	31.47
Comorbidity (associated illness)	
Present (%)	65.24
Category of bed chosen (%)	
Public	66.34
Semi-private	22.06
Private	11.61
Years (%)	
2007	17.34
2008	14.13
2009	17.81
2010	18.10
2011	16.19
2012	16.43

function of attribute m, which are attributes specific to the individual and the diagnosis. In RRM approach, decreasing attribute values of a competing alternative leads to increases in regret associated with the considered alternative when the attribute has a negative sign, such as is the case with the cost attribute.

Applying the HEV variant of the MNL model, we tested the significance of diagnosis, associated illness (comorbidity), and gender for the regret (utility) function of the individual. We also examined the variances in the utility function. The effects of the diagnosis and individual attributes on the probability of choosing the hospital bed were measured by computing pseudo-elasticity[10] (Washington, Karlaftis, and Mannering 2003).

$$E_{x_{inm}}^{P_{in}} = \frac{P_{in}[given x_{inm} = 1] - P_{in}[given x_{inm} = 0]}{P_{in}[given x_{inm} = 0]}, \tag{7}$$

Table 2. Distribution of bed choices by year.

Category of bed chosen (%)	2012	2011	2010	2009	2008	2007
Public	78.01	67.21	64.04	65.5	58.18	64.37
Semi-private	13.47	20.84	22.57	24.83	27.09	23.83
Private	8.52	11.95	13.39	9.67	14.73	11.8
Total	100	100	100	100	100	100

where x_{inm} is the m attribute associated with bed choice i for the nth individual. Average direct pseudo-elasticities for each bed choice i were computed as the average for the entire group of respondents with the same diagnosis during the study period.

IIA is a consequence of the initial assumption that the stochastic terms in the utility functions are independent and extreme value-distributed (Gumbel[11]). The models were tested (Hausman and McFadden 1984) for IIA implications using semi-private and private beds as the omitted alternative for the public beds that characterize the choice model.

Finally, the validation of the goodness-of-fit for model estimation and the direct pseudo-elasticities for the RUM-based model was then repeated for similar attributes in the RRM-based models to compare the effect of different behavioural paradigms on choosing hospital beds.

Majority of the study population were diagnosed with osteoarthritis and were female with higher age group (Table 1).

No systematic trend in hospital bed choice or in hospital admissions was found during the study period (Table 2). However, on average the choice for public bed was the highest followed by the semi-private and private bed category.

IV. Results

The signs were same for both the approaches (Table 3). The coefficient values were relatively higher with less spread in distribution (low standard error) and significant for RU-MNL models compared to RR-MNL models (Table 3). Examination

[10]The classic elasticity measure (Hensher, Greene, and Chorus 2013) cannot be calculated since the probabilities are not differentiable with respect to indicator variables (the variables in the utility function are discrete i.e. 0/1 variables). Hence, the direct pseudo-elasticity (percentage change in probability when an indicator variable is switched (i.e. from 0 to 1 or from 1 to 0)) is computed to measure the marginal effect of an indicator variable on the probability of selecting a certain action (Washington, Karlaftis, and Mannering 2003).

[11]The Gumbel distribution, also known as the *Extreme Value Type I* distribution, is unbounded (defined on the entire real axis), and has the following probability density function:
$f(x) = \frac{1}{\sigma}\exp(-z - \exp(-z))$ where $z = (x-\mu)/\sigma$, μ is the location parameter, and σ is the distribution scale ($\sigma > 0$). The shape of the Gumbel model does not depend on the distribution parameters.

Table 3. Model estimates for the random utility maximization multinomial logit model (RU-MNL) and the random regret minimization multinomial logit model (RR-MNL) (N = *155*).

Model 1 (constant only)			Model 2 (full model)		
Variables (frequency)	RU-MNL (coeff.)	RR-MNL (coeff.)		RU-MNL (coeff.)	RR-MNL (coeff.)
¥ASCpublicbed	0.525*** (0.040)	0.357 (1.35)	Cost	−0.231*** (0.018)	−0.155 (0.616)
¥ASCprivatebed	0.421*** (0.047)	0.291 (1.46)			
	Public bed			Public bed	
ageEffect	0.034*** (0.001)	0.023 (0.066)	ageEffect	0.034*** (0.001)	0.023 (0.066)
genderEffect	0.173*** (0.008)	0.118 (0.375)	genderEffect	0.178*** (0.008)	0.122 (0.369)
comorbidEffect	0.389*** (0.008)	0.266 (0.359)	comorbidEffect	0.391*** (0.008)	0.267 (0.358)
yearEffect	0.087*** (0.002)	0.061 (0.122)	yearEffect	0.088*** (0.002)	0.062 (0.120)
abortionEffect	0.981*** (0.036)	0.695 (1.244)	abortionEffect	1.020*** (0.034)	0.721 (1.25)
anginaEffect	−0.167*** (0.033)	−0.110 (0.651)	anginaEffect	−0.123*** (0.031)	−0.084 (0.645)
jointstiffnessEffect	−0.570*** (0.040)	−0.368 (0.60)	jointstiffnessEffect	−0.528*** (0.039)	−0.344 (0.594)
osteoarthritisEffect	−0.546*** (0.031)	−0.353 (0.582)	osteoarthritisEffect	−0.503*** (0.029)	−0.328 (0.575)
thrombophlebitisEffect	−0.337*** (0.069)	−0.220 (0.612)	thrombophlebitisEffect	−0.295*** (0.068)	−0.195 (0.607)
varicoseveinsEffect	−0.139*** (0.032)	−0.091 (0.664)	varicoseveinsEffect	−0.097*** (0.031)	−0.066 (0.658)
Semi-private bed			Semi-private bed		
ageEffect	−0.049*** (0.002)	−0.032 (0.069)	ageEffect	−0.047*** (0.001)	−0.031 (0.063)
genderEffect	0.423*** (0.009)	0.304 (0.466)	genderEffect	0.433*** (0.008)	0.313 (0.431)
comorbidEffect	0.041*** (0.009)	0.028 (0.399)	comorbidEffect	0.044*** (0.009)	0.030 (0.399)
yearEffect	−0.047*** (0.002)	−0.033 (0.104)	yearEffect	−0.043*** (0.002)	−0.030 (0.086)
abortionEffect	0.234*** (0.042)	0.158 (1.291)	abortionEffect	0.354*** (0.032)	0.239 (1.23)
anginaEffect	0.443*** (0.039)	0.303 (0.806)	anginaEffect	0.563*** (0.028)	0.386 (0.774)
jointstiffnessEffect	0.125*** (0.047)	0.084 (0.745)	jointstiffnessEffect	0.244*** (0.039)	0.164 (0.709)
osteoarthritisEffect	0.123*** (0.037)	0.082 (0.744)	osteoarthritisEffect	0.241*** (0.026)	0.162 (0.717)
thrombophlebitisEffect	−0.274*** (0.085)	−0.180 (0.745)	thrombophlebitisEffect	−0.155* (0.081)	−0.104 (0.711)
varicoseveinsEffect	0.320*** (0.039)	0.217 (0.802)	varicoseveinsEffect	0.442*** (0.027)	0.301 (0.766)
N	155	155		155	155
Loglikelihood function	−647,417.659	−647,431.86		−647,427.229	−647,441.366
Info. Criterion: AIC	8354.060	8354.243		8354.171	8354.353

***, **, * indicate significance at 1%, 5%, and 10% levels.
Standard error: Figures in the parentheses.
¥ Alternative specific constant (ASC)[12]- Comparison: private bed.

of ASC (Model 1) reveals, *ceteris paribus*, the population tended to choose public bed more often than other category of hospital bed. The RU-MNL model results explained plausible behaviour that *ceteris paribus*, the disutility effect was greater (1) for public bed when diagnosed with angina, jointstiffness, osteoarthritis, thrombophlebitis, and varicose veins and (2) for semi-private bed when diagnosed with thrombophlebitis. Increasing age, all else being equal, resulted disutility for semi-private bed. Disutility with year effect was the result of ageing population. The negative coefficient of RR-MNL suggested that regret decreases as the difference in cost between the chosen and the non-chosen alternatives increases, because the non-chosen alternatives added more uncertainty in expectation about the effect of bed choice. On the Akaike's information criterion (AIC) test, RU-MNL was marginally superior on statistical fit compared to RR-MNL.

With HEV variant the predictive power significantly improved for RR-MNL model. The estimates of RU-MNL are having different meanings than those estimated within RR-MNL framework. Utility declined with increased cost but the negative values of RR-MNL indicated minimization of random regret – random regret minimized with decreased cost implying that the choice of private bed was associated with more regret compared to public and semi-private bed (Model 1, Table 4). Compared to private bed the choice of public bed and semi-private bed conferred reduced utility when diagnosed with thrombophlebitis (Model 1, Table 4). On the contrary, for all the diagnoses under study, regret decreased when opted for either public bed or semi-private bed. Regret decreased for female gender with the choice for public bed and the choice of public bed provided better utility for the male gender (Model 1, Table 4) compared to the choice for private bed. The choice of public bed was associated with more regret and more utility while the potential contribution to utility and to regret decreased with age for semi-private bed ((Model 1, Table 4). The

[12] ASC for an alternative captures the average effect of all factors that are not included in the model. Adding this constant makes remaining error have zero mean (Train 2009).

Table 4. HEV models.

	Model 1		Model 2 (gender effect)		Model 3 (gender effect)		Model 4 (comorbidity effect)		Model 5 (comorbidity effect)	
	RU-MNL (coeff.)	RR-MNL (coeff.)	RU-MNL (coeff.)	RR-MNL (coeff.)	RU-MNL: HEV (coeff.)	RR-MNL: HEV (coeff.)	RU-MNL (coeff.)	RR-MNL (coeff.)	RU-MNL: HEV (coeff.)	RR-MNL: HEV (coeff.)
Cost	−1.004*** (0.030)	−1.409*** (0.013)	0.061*** (0.022)	0.059 (0.872)	−0.532*** (0.023)	−0.702*** (0.030)	0.037* (0.022)	0.052 (0.940)	−0.436*** (0.018)	−1.210*** (0.023)
	Public bed		Public bed				Public bed			
ageEffect	0.001*** (0.000)	0.005***(0.000)	0.104*** (0.002)	0.074 (0.107)	0.076*** (0.003)	0.084*** (0.003)	0.089*** (0.002)	0.063 (0.096)	0.003*** (0.000)	0.007*** (0.001)
genderEffect	0.076*** (0.011)	−0.122*** (0.010)	Gender = Female effect				0.263*** (0.010)	0.186 (0.570)	0.110*** (0.013)	−0.045*** (0.014)
comorbidEffect	0.038*** (0.010)	−0.002 (0.008)	0.458*** (0.011)	0.315 (0.513)	0.023** (0.010)	0.018* (0.010)	Comorbidity effect			
yearEffect	0.020*** (0.003)	−0.012*** (0.002)	0.111*** (0.003)	0.081 (0.178)	0.033*** (0.003)	0.027*** (0.003)	0.140*** (0.003)	0.105 (0.201)	0.039*** (0.003)	0.011*** (0.003)
abortionEffect	0.113* (0.067)	0.053*** (0.018)	1.568*** (0.038)	1.166 (1.522)	0.953*** (0.057)	0.661*** (0.069)	0.813*** (0.039)	0.582 (1.643)	1.002*** (0.045)	0.047 (0.032)
anginaEffect	0.068 (0.069)	−0.127*** (0.016)	−0.027 (0.039)	−0.008 (0.914)	0.520*** (0.068)	0.169** (0.083)	0.026 (0.035)	0.029 (0.980)	0.098*** (0.045)	−0.022 (0.030)
jointstiffnessEffect	0.079 (0.071)	−0.151*** (0.043)	0.080 (0.050)	0.065 (0.986)	0.488*** (0.075)	0.181** (0.084)	−0.222*** (0.048)	−0.135 (0.914)	0.94*** (0.057)	−0.005 (0.037)
osteoarthritisEffect	0.012 (0.069)	−0.153***(0.012)	−0.243*** (0.033)	−0.149 (0.852)	0.454*** (0.068)	0.116 (0.083)	−0.534*** (0.033)	−0.335 (0.847)	0.921*** (0.045)	−0.063** (0.028)
thrombophlebitisEffect	−0.031 (0.189)	−0.163 (0.107)	−0.066 (0.087)	−0.033 (0.900)	0.477** (0.084)	0.131 (0.105)	−0.366*** (0.078)	−0.227 (0.866)	0.984*** (0.058)	0.006 (0.054)
varicoseveinsEffect	0.051 (0.069)	−0.121*** (0.016)	0.232*** (0.036)	0.169 (1.025)	0.651*** (0.063)	0.307*** (0.077)	−0.101*** (0.037)	−0.055 (0.939)	0.928*** (0.048)	−0.031 (0.032)
	Semi-private bed		Semi-private bed				Semi-private bed			
ageEffect	−0.003*** (0.000)	−0.003***(0.001)	0.012*** (0.002)	0.009 (0.089)	0.087*** (0.004)	0.099*** (0.004)	−0.044*** (0.002)	−0.028 (0.087)	−0.001*** (0.000)	−0.002*** (0.000)
genderEffect	0.090*** (0.011)	0.518***(0.010)	Gender = Female effect				0.464*** (0.011)	0.343 (0.670)	0.120*** (0.013)	0.419*** (0.012)
comorbidEffect	0.023** (0.010)	−0.021***(0.008)	0.014 (0.012)	0.012 (0.561)	−0.056*** (0.011)	−0.073*** (0.012)	Comorbidity effect			
yearEffect	0.014*** (0.003)	−0.024*** (0.003)	0.008*** (0.003)	0.003 (0.120)	−0.009** (0.004)	−0.018*** (0.004)	−0.029*** (0.003)	−0.022 (0.128)	0.032*** (0.003)	0.002 (0.003)
abortionEffect	0.092 (0.070)	−0.737*** (0.021)	0.927*** (0.034)	0.688 (1.465)	0.803*** (0.062)	0.480*** (0.075)	0.109*** (0.039)	0.010 (1.765)	1.007*** (0.045)	−0.358*** (0.037)
anginaEffect	0.760*** (0.053)	−0.198*** (0.019)	0.649*** (0.037)	0.480 (1.071)	0.674*** (0.064)	0.383*** (0.076)	0.777*** (0.033)	0.574 (1.249)	1.309*** (0.039)	0.099*** (0.030)
jointstiffnessEffect	0.775*** (0.056)	−0.227*** (0.044)	0.754*** (0.050)	0.558 (1.074)	0.783*** (0.068)	0.572*** (0.072)	0.480*** (0.051)	0.360 (!.149)	1.266*** (0.052)	0.112*** (0.037)
osteoarthritisEffect	0.701*** (0.053)	−0.220*** (0.015)	0.664*** (0.030)	0.490 (1.069)	0.853*** (0.057)	0.611*** (0.067)	0.386*** (0.031)	0.293 (1.109)	1.252*** (0.039)	0.072** (0.029)
thrombophlebitisEffect	−0.010 (0.213)	−0.256** (0.108)	0.055 (0.106)	0.066 (1.005)	0.623*** (0.083)	0.325*** (0.102)	−0.088 (0.094)	−0.030 (1.083)	1.025*** (0.061)	0.067 (0.055)
varicoseveinsEffect	0.725*** (0.053)	−0.209*** (0.018)	0.899*** (0.031)	0.667 (1.134)	1.192*** (0.047)	0.961*** (0.056)	0.380*** (0.036)	0.290 (1.155)	1.244*** (0.042)	0.075** (0.032)
N	*155*	155	84	84	84	84	78	78	78	78
Log-likelihood function	−588,359.432	−581,328.554	−394,381.871	−394,420.065	−361,011.202	−360,802.848	−405,225.438	−405,270.574	−378,994.032	−368,234.424
Info. Criterion: AIC	7592.031	7501.310	9390.497	9391.406	8596.005	8591.044	10,390.883	10,392.039	9718.334	9442.447
Error variance^										
Public bed	0.057*** (0.001)	0.058*** (0.003)			0.059*** (0.003)	0.059*** (0.004)			0.059*** (0.006)	0.057*** (0.001)
Semi-private bed	0.60*** (0.017)	0.574*** (0.010)			0.621*** (0.023)	0.743*** (0.028)			0.279*** (0.013)	0.440*** (0.008)
McFadden pseudo R^2	0.31	0.32			0.33	0.33			0.32	0.34

***, **, * indicates significance at 1%, 5%, and 10% levels.
^ indicate sq. of θ; scale parameter of private bed normalized to 1
Figures in the parentheses: standard error.

goodness-of-fit for the model with the data was better with RR-MNL (Model 1, Table 4).

Models 2 and 3, Table 4 revealed the gender effect on other attributes of bed choice alternatives. Though the signs of the coefficients were same for RU-MNL and RR-MNL, the predictive power was statistically significant with RU-MNL model (Model 2, Table 4). With HEV variant, the predictive power for cost with RR-MNL improved significantly (31.95%) compared to RU-MNL and also the goodness-of-fit for the model with the data (Model 3, Table 4). The comorbidity effect was also better reflected with the HEV variant of RR-MNL model – an impressive predictive gain for cost compared to the RU-MNL counterpart and so, also the goodness-of-fit for the model with the data (Model 5, Table 4).

The sign of the cost changed for both RU-MNL and RR-MNL variants (Model 2 and Model 4, Table 4) when gender and comorbidity effect influenced the attributes. Overall negative expressions (Model, 1, Model 3, and Model 5, Table 4) for cost indicated that the heteroskedastic effect reduced the disutility for public and semi-private bed and minimization of random regret for public and semi-private bed compared to private bed choice. The cross–individual heteroskedasticity, when normalized to 1 for private bed, the error variance of RR-MNL models was larger with gender effect and comorbidity effect suggesting scale heterogeneity (attribute thresholds) in the presence of preference heterogeneity were better captured with RR-MNL models.

The absolute magnitude of pseudo-elasticities between RU-MNL and RR-MNL was almost similar (Table 5). For illustration, the results (Table 5) are interpreted for RU-MNL as – a 10% increase in the price of semi-private bed results, on average, 18% reduction in the probability of choosing semi-private bed, given the choice among bed categories and holding all other influences constant. In the context of RR-MNL model, this 10% increase in the price of semi-private bed takes into account the level of the cost associated with other categories of available beds. More specifically, 17% reduction in the probability of choosing semi-private bed in RR-MNL explicitly accounted the levels of the cost associated with available alternatives (bed categories), in recognition of regret associated with the inadvertent choice of wrong alternatives. A 10% higher pseudo-elasticity of RR-MNL than the RU-MNL indicated accounting for

Table 5. Difference in pseudo-elasticities.

	Public bed	Semi-private bed	Private bed	Public bed	Semi-private bed	Private bed	Public bed	Semi-private bed	Private bed
	RU-MNL			RR-MNL			Difference [RU-MNL − RR-MNL]		
Semi-private bed	0.05	−0.18	0.05	0.06	−0.17	0.07	−0.01	−0.01	−0.02
Private bed	0.06	0.06	−0.41	0.07	0.08	−0.34	−0.01	−0.02	−0.07
	RU-MNL (HEV)			RR-MNL (HEV)			Difference [RU-MNL − RR-MNL]		
Semi-private bed	0.63	−1.91	0.38	0.05	−0.18	0.06	0.58	−1.73	0.32
Private bed	0.18	0.14	−1.32	0.04	0.05	−0.37	0.14	0.09	−0.95
	RU-MNL (HEV) – Gender effect			RR-MNL (HEV) – Gender effect			Difference [RU-MNL − RR-MNL]		
Semi-private bed	0.27	−1.61	0.13	−0.02	0.07	−0.02	0.29	−1.68	0.15
Private bed	0.11	0.08	−0.85	−0.02	−0.02	0.16	0.13	0.10	−1.01
	RU-MNL (HEV) – comorbidity effect			RR-MNL (HEV) – comorbidity effect			Difference [RU-MNL − RR-MNL]		
Semi-private bed	0.54	−2.40	0.17	−0.01	0.06	−0.01	0.55	−2.46	0.18
Private bed	0.10	0.09	−0.65	−0.02	−0.02	0.14	0.12	0.11	−0.79

the possibilities that the wrong choice could have amplified the behavioural response that conventionally attributed to the utility-based elasticity.

In line with the model results (Table 4), the pseudo-elasticities for semi-private and private bed were larger in the HEV variants of RR-MNL models compared to the counterparts of RU-MNL suggesting varying behavioural responses to a given change in a specific policy instrument across the three categories of hospital bed choice. The choice for semi-private bed was more elastic in HEV variant of RU-MNL models.

V. Discussion

We compared the utility maximization and regret minimization based choice models' sensitivity to individual heterogeneity. The utility maximization and regret minimization approaches paradigm of choice modelling were compared in regard to the variances in the utility (regret) function, goodness-of-fit and predicted marginal effects (pseudo-elasticity) of additional payment. We illustrated the predictive power of Random Utility Maximization Multinomial Logit Models (RU-MNL) and Random Regret Minimization Multinomial Logit Models (RR-MNL) on the hospital bed choice in Switzerland.

Our data were having only the universal choice set of three alternatives. Our attributes were cost, diagnosis, and comorbidity. We used age and gender as demographic variables. The goodness-of-fit for our data in both the approaches was excellent, however, heteroskedastic variants of RR-MNL were having much better goodness-of-fit compared to its RU-MNL counterparts. Such findings supports Chorus (2012) who had shown that regret minimization models on average fit better relative to utility-based models in the context of revealed preference data.

Consistent with the argument of Zeelenberg and Pieters (2007) and in line with the evidences from previous studies (Brehaut et al. 2003; Djulbegovic et al. 1999; Sorum et al. 2004; Ziarnowski, Brewer, and Weber 2009), we have also found the better performance of regret-based models. Although our findings support existing literatures, settings influence model performance.

The marginal effects of different attributes were also better reflected with the choice alternatives in regret-based models – suggesting that random regret as preferred representation of behavioural responses in this empirical study. Such findings raise an important question of which elasticity estimates should be of policy relevance. This reflection is congruent with the argument (Boeri et al. 2013) that utility maximization framework is not the only driver of choices for the individuals in all situations of life and also supports the argument (Smith 1996) that utility theory-based measures of health do not necessarily reflect the true preferences of the individual.

The limitations of the data did not allow inclusion of socioeconomic characteristics of the individual in choice-set composition nor could this study include the attributes ascribed to different choices. Thus, additional cost was the only parameter to reflect the variances in choice alternatives. The cross-sectional nature of the data did not allow this study to examine the *ex-ante* effect of condition at discharge when many such admissions were repeat episodes for the sample population.

Being non-nested models, the goodness-of-fit was assessed with penalization of log-likelihood functions of each models and AIC. McFadden's R-squared values from 0.2 to 0.4 indicate an excellent (in McFadden's own words) model fit, thus the data were apt for both paradigms.

VI. Conclusion

This study introduces random regret minimization-based DCEs to health systems. We have demonstrated the predictive capability of two different approaches in modelling choice behaviour. The model fitness parameters indicate that random regret-based models perform better in reflecting attribute effects. Hence, regret-based choice modelling does have the potential to capture significant loss (gain) in choice situations and can be used as a complimentary to conventional utility-based modelling. Further, in the situation of uncertainty in outcome prevalent in healthcare services consumption and difficulties in choice making for reasons of information asymmetry, it is unlikely that the axiom of expected utility theory remains consistent in all choice situations. Notwithstanding the limitations of using the grouped data, this study demonstrates application of regret-based choice modelling approach in health systems.

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Author's contributions

PP generated the concept, carried out the analysis of the datasets, interpreted the results of the analysis and drafted the manuscript. CB created the data subsets. MM facilitated in sourcing the datasets. HV organized the datasets. HV finally edited the manuscript. All authors have read and approved the final manuscript.

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