Modeling experienced accessibility for utility-maximizers and regret-minimizers

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Abstract

This paper argues that there is a discrepancy between what Logsum-measures of accessibility aim to measure (experienced utility) and what they actually measure (decision-utility). The latter type of utility refers to the evaluation of an alternative that is used to arrive at a decision, while the formerrefers to the evaluation of a chosen alternative after the choice has been made. We argue that accessibility should preferably be conceptualized and operationalized in terms of experienced utility, but that this type of utility is difficult to measure. Motivated by these observations we show, taking the Logsum as a starting point, how its building blocks (parameters estimated from choice patterns) can be used to construct closed-form and easy to compute accessibility measures that provide an approximation of experienced utility.Using a small-scale case-study building on departure time-choice data, we illustrate the working of the developed accessibility-measures and highlight how they differ from the Logsum-approach.

Keywords: Accessibility; Logsum; Experienced utility; Decision-utility; Regret

1. Introduction

Accessibility is “a slippery notion” (Gould, 1969). It should therefore come to no surprise that it has been measured in numerous ways (see Geurs & van Wee (2004) for a relatively recent overview). One of the more popular accessibility-measures – both in- and outside academia –is the Logsum, which over the years has been used successfully for the appraisal of various land-use/transport policy strategies (e.g. Handy &Niemeier, 1997; Waddell et al., 2007; de Bok, 2009; Geurs et al., 2010). The Logsum has been successfully incorporated in a number of transport model systems, including TRESIS (Hensher et al., 2004) and LUSTRE (e.g., Safirova, 2007).[1] It is widely acknowledged (e.g. de Jong et al., 2007; Chorus & Timmermans, 2009) that this popularity arises from the Logsum’s theoretical advantages over more ad-hoc accessibility measures. More specifically, Logsum-measures provide a closed-form expression for accessibility based on a solid foundation in discrete choice theory (Ben-Akiva & Lerman, 1985) and neo-classical consumer surplus theory (Small & Rosen, 1981; McFadden, 1981).

The Logsum[2] is defined as the expected maximum utility associated with a traveler’s choice set. The expectation refers to the fact that the analyst only ‘knows’ the traveler’s utilities up to a random error. As such, he or she does not know for sure which alternative will be chosen, and what will be the exact utility associated the chosen alternative. At least implicitly, this definition suggests that the utility a traveler experiences upon executing an alternative from the choice set (i.e. by traveling) is measured, which would indeed constitute an intuitive measurement of accessibility. However, the Logsum-measure of accessibility is in fact not necessarily based on the utility travelers actually experience, but on the utility that has presumably driven their choice-behavior (in the form of parameters estimated from their choices). In the behavioral economics community, this latter type of utility is generally called *decision utility*, while the former type of utility which is referred to as *experienced utility* (Kahneman et al., 1997). The implicit assumption underlying the Logsum-notion is that decision utilities (applied by the traveler to arrive at a decision) are the same as experienced utilities (experienced by the traveler during the execution of alternatives). However, it goes without saying that these utilities refer to intrinsically different behavioral notions.

[1] On the other hand, even though many transport and land use/transport models include logsums, the use of logsums in project appraisal is not standard practice (de Jong et al., 2007).
[2] See section 2 for a more in-depth formal presentation of the Logsum-approach to measuring accessibility.

It goes without saying that accessibility measures (or welfare measures in general) should preferably be based on experienced utility, not decision utility. However, it is also clear that direct measurements of experienced utility are very hard to obtain in a sound and internally consistent way; hence most economists' preference for working with the concept of decision utility, as it allows them to use choices as a rigorous unit of measurement (e.g. Stigler, 1950). In sum, there appears to be a discrepancy between what the Logsum actually measures (decision utility), and how it is used and interpreted in the context of accessibility appraisal (as a measure of experienced utility).

This paper aims to show how this discrepancy can be resolved to some extent: we take the Logsum as a starting point, and show how its building blocks (parameters estimated from choice patterns) can be used to construct closed-form and easy to compute accessibility measures that provide an approximation of experienced utility. We take a two-step approach: first, in line with a large body of literature from the field of behavioral decision theory (e.g. Payne et al., 1999; Lichtenstein & Slovic, 2006) we assume that the *preferences* a decision-maker uses to arrive at a decision are likely to differ to some extent from preferences used to assess the performance of a chosen alternative. Second, we allow for the situation where *evaluation-rules* may differ between the situation where an alternative is chosen and the situation where a chosen alternative is executed. Specifically, we propose a closed-form accessibility measure that assumes choices may be based on a regret-minimization evaluation rule instead of a utility-maximization evaluation rule, while the performance of executed alternatives is evaluated based on a utility-maximization evaluation rule[3].

The choice for considering a regret-based decision-making perspective is based on two arguments: first, there is a large body of literature from various corners of the social sciences supporting the hypothesis that the minimization of anticipated regret is a very important determinant of choice-behavior (e.g., Loomes and Sugden, 1982; Simonson, 1992; Connolly,

[3] It may of course be hypothesized that in addition to *decisions* also *experiences* are based on regret-based, rather than utility-based rules. However, doing so would break the elegant formal relation between accessibility on the one hand and welfare economic theory on the other hand (such as the translation of expected utility change into consumer surplus change in monetary terms). Since these links are crucial for the assessment of benefits associated with (land use-) transport policies, we in this paper work with the hypothesis that experiences are evaluated using utility-based rules, while decisions may be based on regret-based as well as utility-based rules.

2005). Take for example Coricelli et al. (2005) who, using neuroimaging techniques, show that the area of the human brain that is active when decision-makers experience regret after having made a (poor) choice, is also highly active split seconds *before* they make a choice. In their words "anticipating regret is a powerful predictor of future choices". Second, and this is a more pragmatic reason for adopting a regret-based approach, a generic regret-based discrete choice-modeling approach for the analysis of risky as well as riskless choice[4] has recently been developed and successfully applied in a variety of travel choice-contexts (Chorus, 2010). This Random Regret Minimization-approach has important formal similarities with conventional utility-based discrete choice-approaches (such as the MNL-model (McFadden, 1974)) and as such can be relatively easily combined with these conventional approaches to form integrative accessibility measures.

The remainder of this paper is organized as follows: section 2 discusses the Logsum-measure. Section 3 presents an accessibility measure that is based on the notion that preferences are volatile to some extent. Section 4 presents an accessibility measure that assumes a regret-based evaluation rule at the level of decisions, and a utility-basedevaluation rule at the level of experiences. Section 5 illustrates the working of the developed accessibility-measures using a small-scale case-study. Section 6 presents conclusions as well as recommendations for future research.

2. The Logsum as a measure of accessibility benefits

Assume the following choice situation: a decision-maker faces a set of *J* alternatives, each being described in terms of *M* attributes x_m. Random Utility Theory (McFadden, 1974) postulates that a decision-maker chooses alternative *i* from the set when its random utility ζ_i is larger than that of

[4] It is important to note here that, although most people would associate the notion of regret with risky choice in particular, it is also readily applicable to riskless choices (i.e., choices where the values of the attributes of alternatives are known with certainty), as long as alternatives are defined in terms of multiple attributes. This follows from the fact that the process of making tradeoffs between different attributes of different alternatives implies that – in most situations – one has to decide to live with a suboptimal performance on one or more attributes in order to achieve a satisfactory outcome on other attributes. It is this situation that can be postulated to cause regret at the level of specific attributes (see Section 4.1 for a more formal and detailed exposition of this argument).

all other alternatives in the set. Random utility consists of a deterministic part V_i and a random error ε_i, the latter representing the inability of the analyst to faultlessly assess the decision-makers utility (in other words: it represents unobserved heterogeneity among decision-makers). Deterministic utility in turn is generally formulated as a linear-additive function of tastes β_m and attributes x_m although more complicated forms are possible. In notation: $U_i = V_i + \varepsilon_i = \sum_{m=1..M} \beta_m x_{im} + \varepsilon_i$ (note that we ignore in this and subsequent equations the subscript for the decision-maker, for clarity of presentation). Under the assumption that ε_i is i.i.d. Extreme Value Type I-distributed with variance equaling $\pi^2/6$, choice probabilities P_i are given by elegant logit-probabilities (McFadden, 1974): $P_i = \exp(V_i) \Big/ \sum_{j=1..J} \exp(V_j)$.

In the context of Random Utility Theory, accessibility (*Acc*) has been defined as the expected maximum utility associated with the decision-maker's choice set. Importantly: the expectation refers to imperfect knowledge from the side of the analyst, not from the side of the traveler. Under the prevailing error-term assumptions, this expected maximum in turn is given by the natural logarithm of the denominator of this fraction, which is called the Logsum (e.g., Ben-Akiva & Lerman, 1985):

$$Acc = E\left[\max_{j=1..J}\{U_j\}\right] = \int_{\boldsymbol{\varepsilon}} \left[\left(\max_{j=1..J}\{U_j\}\right) \cdot f(\boldsymbol{\varepsilon})\right] d\boldsymbol{\varepsilon} = \ln\left[\sum_{j=1..J} \exp(V_j)\right] + C \qquad (1)$$

The accessibility benefits of a given land use-transport strategy can then be computed by taking the difference in the accessibility with and without the implementation of the strategy. When this is done, the constant *C* will cancel out of the equation. It may be noted that, under the fairly restrictive assumption that utility increases linearly in income, accessibility benefits as measured by the Logsum can very easily be translated to monetary terms by just dividing it by the marginal utility of income (for which one can use the estimated cost coefficient). In this paper, we refrain from this translation and focus on accessibility benefits in terms of utility-changes only.

3. Incorporating changes in preferences between choice and experience

A traveler's preferences may differ between the moment of choice and the moment of execution of the chosen alternative. There may several reasons for this. First, it is widely acknowledged in the behavioral decision-making literature that people often *construct* their preferences when faced with a choice, rather than simply *applying* already existing preferences to the choice situation at hand (e.g. Payne et al., 1999; Lichtenstein & Slovic, 2006). As a result, there may be a difference between these constructed preferences and those that apply when an experience is evaluated without the aim of making a choice. Especially when one is using stated data to estimate preferences (like in the SC-experiment used in this study), this difference may be substantial due to the possible existence of all sorts of artificial effects on preference formation that are specific to the particular experimental set-up (see Hensher (2010) for a recent review of such effects). Second, preferences may also change over time due to intrinsic stochasticity, especially when there is a time gap between the moment of choice and the moment of experience (e.g. Hey, 1995; Hoeffler & Ariely, 1999). It is worthwhile at this point to note that a traveler that makes the same trip frequently (e.g., his or her commute to and from work) can of course learn over time how attractive a given option is, which would imply a decreasing (over time) volatility of preferences. However, in the context of the introduction of new or improved land use-transport services there is likely going to be a substantial amount of preference volatility, especially shortly after the introduction. For obvious reasons, learning effects are not applicable when stated data are used, but they may be important in the context of revealed data-analysis.

In line with Manski's ideas (1977), we adopt the perspective that within a discrete choice-model this volatility of preferences is captured in the error term. More specifically, we assume that the extent to which preferences are invariant between the moment of choice and the moment of experience is captured by stable (invariant) betas, and that the extent to which preferences are volatile is captured by the notion that the error associated with an alternative's utility may differbetween the moment of choice and the moment of experience.

In notation, the above line of reasoning can be put as follows, in the context of the choice situation described in section 2: again, when faced with a choice from *J* alternatives, each being described in terms of *M* attributes x_m, the traveler uses a preference-set represented by estimable parameters β_m (for $m = 1 \ldots M$) and a random error ε_i (i.i.d.-Extreme Value Type I-distributed) to evaluate some alternative *i*. When the same alternative is evaluated during or after experiencing it, the same traveler uses a preference-set represented by the same parameters β_m (for $m = 1 \ldots M$) but a different random error ν_i . This error is also drawn from an i.i.d.-Extreme Value Type I-distribution with the same variance as that of ε_i. The error is drawn independently from ε_i.

The accessibility associated with the choice set is again taken to be the expected utility a traveler derives from the choice set, which is in turn defined as the utility he or she derives from experiencing the alternative chosen from this set. Since the choice is only known up to a probability, accessibility is defined by integrating out the two mutually independent error-vectors. This implies the following formulation of accessibility:

$$Acc = \int_{\boldsymbol{\varepsilon}}\int_{\mathbf{v}}\left[\left(\sum_{j=1..J}\left(I_j\left(\boldsymbol{\beta},\boldsymbol{\varepsilon}\right)\right)\cdot\left(U_j\left(\boldsymbol{\beta},\mathbf{v}\right)\right)\right)\cdot f\left(\boldsymbol{\varepsilon}\right)f\left(\mathbf{v}\right)\right]d\boldsymbol{\varepsilon}d\mathbf{v}$$

$$= \sum_{j=1..J}\left[P_j\left(\boldsymbol{\beta}\right)\cdot\left(V_j\left(\boldsymbol{\beta}\right)\right)\right]+C \tag{2}$$

Here, vector $\boldsymbol{\beta}$ contains parameter estimates (obtained from estimating the MNL-based choice model on observed choices). I_j is an indicator function which equals one if, given the vector of estimated parameters and the vector of random errors ε, alternative *j*'s random utility U_j is larger than the utilities of all other alternatives in the set. U_j, V_j, P_j are as defined in section 2 in the context of alternative *i*.

The crucial difference between this formulation and the Logsum is that the expectation of the maximum decision-utility is taken separately from the expectation of experienced-utility, because both are a the result of integration over different errors (yet drawn from the same distribution with the same variance). In case the two errors are assumed to be equal to one another (implying the assumption that decision-utility equals experienced utility), this formulation reduces to the conventional Logsum-measure presented in section 2.

4. Incorporating changes in evaluation rules between choice and experience

This section takes the difference between decisions and experience one step further: in addition to the assumption that preferences are assumed to differ between the moment of decision and the moment of experience, we now also allow for the possibility that evaluations preceding decisions may be based on a different rule than evaluations during or following experiences. Although many alternative decision-rules may be applicable, we here focus on the example where the evaluation-rule used for arriving at a decision may be based on regret-minimization premises rather than utility maximization premises[5], whereas the evaluation rule used to judge the performance of a chosen alternative during execution is utility-based. That is, while Eq. 2 assumes RUM-based decision-making and RUM-based experience evaluation, our next accessibility equation assumes RRM-based decision-making and RUM-based experience evaluation. It should be noted that the general issue we aim to highlight (evaluation rules may differ between the moments of decision and experience) is much broader than the regret-utility contrast used in the remainder of this paper. Section 4.1 presents the Random Regret Minimization (RRM)-approach to discrete choice modeling, followed by section 4.2 which integrates RRM with the concept of experienced utility.

4.1 Regret-Minimization as a choice rule[6]

Assume the same choice situation used earlier in this paper: a decision-maker faces a set of *J* alternatives, each being described in terms of *M* attributes x_m. Assume also that the attributes are comparable across alternatives. The RRM-model postulates that when choosing between alternatives, decision-makers aim to minimize anticipated random regret, and that the level of anticipated random regret that is associated with a considered alternative *i* is composed out of a systematic regret R_i and an i.i.d. random error ε_i which represents unobserved heterogeneity in regret and whose negative is Extreme Value Type I-distributedwith variance $\pi^2/6$.

[5] Whether or not this assumption is reasonable, will of course have to be determined on a case-by-case base; an intuitive candidate for selecting one evaluation rule (used for arriving at a decision) over another one is the goodness of fit of different evaluation rules (translated into a discrete choice-model form) with relevant choice data.

[6] See Chorus (2010) for a more detailed introduction to the RRM-approach, as well as an in-depth theoretical and empirical comparison with the RUM-approach to travel choice modeling.

Systematic regret is in turn conceived to be sum of all so-called binary regrets that are associated with bilaterally comparing the considered alternative with each of the other alternatives in the choice set. The level of binary regret associated with comparing the considered alternative *i*with another alternative *j* equals the sum of the regrets that are associated with comparing the two alternatives in terms of each of their *M* attributes. This attribute level-regret in turn is formulated as follows: $R_{i\leftrightarrow j}^{m} = \ln\left(1+\exp\left[\beta_m \cdot \left(x_{jm} - x_{im}\right)\right]\right)$. Note that also the sign of parameters is estimated (i.e., no *a priori* sign expectations need to be formulated). See Figure 1 for a visualization of this formulation of attribute-level regret.Systematic regret then becomes: $R_i = \sum_{j\neq i} \sum_{m=1..M} \ln\left(1+\exp\left[\beta_m \cdot \left(x_{jm} - x_{im}\right)\right]\right)$. Acknowledging that minimization of random regret is mathematically equivalent to maximizing the negative of random regret, choice probabilities may be derived using a variant of the multinomial logit-formulation: the choice probability associated with alternative *i* equals $P_i^R = \exp\left(-R_i\right) \Big/ \sum_{j=1..J} \exp\left(-R_j\right)$.

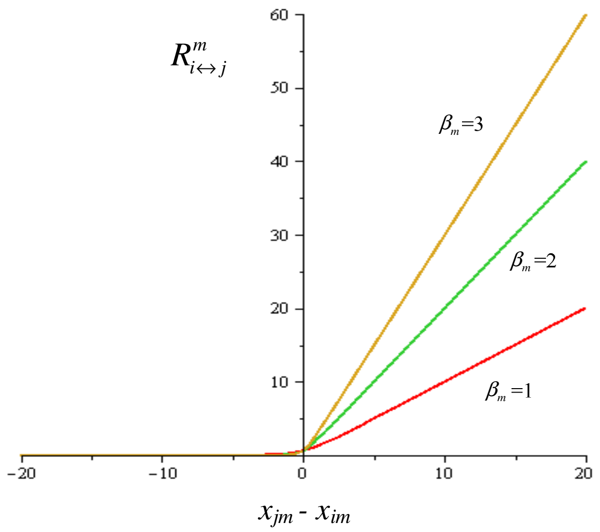

Figure 1: A visualization of attribute level-regret $R_{i\leftrightarrow j}^{m} = \ln\left(1+\exp\left[\beta_m \cdot \left(x_{jm} - x_{im}\right)\right]\right)$

Note that the resulting likelihood function is smooth and that the model can be coded and estimated using standard discrete choice-software packages. Recent studies (Chorus, 2010; Hensher et al., under review) have highlighted the promising empirical performance of RRM (also when compared to equally parsimonious RUM-models) in the context of car-type choices, mode/route choices, parking choices and shopping location-choices. As discussed more in-depth in Chorus (2010), the main difference between RRM and its utilitarian (and equally parsimonious) counterpart – RUM's linear-additive MNL-model – lies in the fact that the RRM-based MNL-model does not exhibit the IIA-property (which states that the choice-probability ratio of any two alternatives is unaffected by the presence and performance of a third alternative), even when errors are i.i.d. That is, the ratio of choice probabilities of any two alternatives i and j depends on the performance of these alternatives relative to one another as well as relative to each other alternative k in the set. This follows directly from the specification of the regret-function, which postulates that the regret associated with any alternative in the set is a function of its performance relative to each of the other alternatives available.

Second, in contrast with linear-additive utilitarian choice-models, the model based on regret minimization implies semi-compensatory behaviour. This is a direct result of the convexity of the regret-function depicted in Figure 1: 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 deteriorating to a similar extent the performance on another equally important attribute on which the alternative has a poor performance relative to other alternatives may generate substantial increases in regret. As a result, the extent to which a strong performance on one attribute can make up for a poor performance on another depends on the relative position of each alternative in the set.More specifically, and in line with empirical evidence from the field of consumer choice (e.g. Simonson, 1989; Wernerfelt, 1995; Kivetz et al., 2004), RRM captures a substitution effect called the compromise effect. This effect states that alternatives with an 'in-between' performance on all attributes, relative to the other alternatives in the choice set, are generally favored by choice-makers over alternatives with a poor performance on some attributes and a strong performance on others.

4.2 *Accessibility when decisions are based on regret-minimization*

Take a set of parameters β_m^R resulting from estimation of an RRM-model, and a set of parameters β_m^U resulting from estimation of its RUM-based counterpart on the same data. Denote unobserved preferences for alternative *i* by ε_i (unobserved preference at the time of the decision) and ν_i(unobserved preference at the time of the experience), respectively. We assume that ν_i and the negative of ε_i are drawn from independent i.i.d.-Extreme Value Type I-distributions with variance $\pi^2/6$. Building on the formulations presented in section 3, accessibility derived from a choice set by a traveler that chooses based on regret-minimization, but evaluates chosen options in terms of their utility, can be written as follows:

$$
\begin{aligned}
Acc &= \int_{\boldsymbol{\varepsilon}}\int_{\mathbf{v}}\left[\left(\sum_{j=1..J}\left(I_j^R\left(\boldsymbol{\beta}^{\mathbf{R}},\boldsymbol{\varepsilon}\right)\right)\cdot\left(U_j\left(\boldsymbol{\beta}^{\mathbf{U}},\mathbf{v}\right)\right)\right)\cdot f\left(\boldsymbol{\varepsilon}\right)f\left(\mathbf{v}\right)\right]d\boldsymbol{\varepsilon}d\mathbf{v} \\
&= \sum_{j=1..J}\left[P_j^R\left(\boldsymbol{\beta}^{\mathbf{R}}\right)\cdot\left(V_j\left(\boldsymbol{\beta}^{\mathbf{U}}\right)\right)\right]+C
\end{aligned}
\tag{3}
$$

Symbols are as presented directly after equation (2). Vector $\boldsymbol{\beta}^R$ contains parameter estimates obtained from estimating the regret-based model on observed choices, $\boldsymbol{\beta}^U$ contains parameter estimates obtained from estimating the utility-based model on the same observed choices. I_j^R is an indicator function which equals one if, given the vector of estimated parameters and conditional on the vector of random errors ε, alternative *j*'s random regret R_j is smaller than the regrets of all other alternatives in the set. R_j, V_j, P_j^R are as defined previously.

5. An illustrative case-study

This section shows how the three accessibility measures presented in the previous sections (equations (1), (2) and (3) respectively) may differ from one another, in the context of estimation results based on departure time choice data. The emphasis here is on showing *that* the three measures may lead to different planning decisions, although an attempt is also made to discuss *in what ways* and *to what extent* the measures differ, and what are the causes of these differences. However, since it is to be expected that the ways in which the three measures differ is highly dependent on prevailing preference structures and choice set composition, we refrain from making too many general statements based on the one case study presented here.

Data is collected using a Stated Choice-experiment, performed for the Dutch Ministry of Transport, Public Works and Water Management (currently: Ministry of Infrastructure and Environment). Travelers were asked to choose between three departure times for their daily commute: they could choose to depart at or close to their regular hour, or considerably earlier or later (and face reduced travel times). Each of the options is defined in terms of travel time (in minutes, for both the morning and the evening), time spent in traffic jams (in minutes, for both the morning and the evening) and resulting amount of time at work (minutes). In light of this paper's scope, we do not elaborate the setup of the experiment and characteristics of the response group. See de Jong et al. (2003) for a detailed discussion of these and related aspects. We used for our analyses only commuters that had indicated that traveling by public transport was not an option for them. In other words, their choice set consisted of the three presented departure time-alternatives only. This subset consisted of 883 choices, which were analyzed using the free software package BIOGEME (Bierlaire, 2003, 2008). Table 1 shows results of the estimated MNL-models (RRM- and RUM-based).

Note that, to reflect the panel nature of the dataset (each respondent made multiple choices), robust t-values are reported. These are computed based on the robust variance-covariance matrix of estimates (or: sandwich estimator), and allow for non-severe misspecification errors related to the characteristics of the postulated distributions for the error terms (see Bierlaire (2008) for an in-depth formal treatment of how to compute these t-values). In our case, the fact that we assume independent errors for different choices made by the same individual constitutes such a non-severe misspecification. Note also that in this model of departure time choice, accessibility will include time of day: if peak and off-peak travel times would be equal, most commuters would travel in the peak.In line with expectations, departing at another than the regular time comes with a penalty, as implied by the large and significant constant for regular departure time. Time spent in traffic jams during the morning as well as the evening commute is valued negatively. Other parameters are insignificant at any reasonable level of significance. The RRM-model seems to have a very slight edge over the RUM-model, although the difference is negligible[7].

Table 1: RRM-MNL versus RUM-MNL

	RRM		**RUM**	
Attribute	*beta*	*t-value*	*beta*	*t-value*
Constant (regular departure time)	**1.48**	**16.11**	**1.47**	**16.02**
Travel time (morning)	-0.00376	-1.27	-0.00579	-1.48
Time spent in traffic jam (morning)	**-0.0264**	**-4.62**	**-0.0377**	**-4.67**
Travel time (evening)	-0.00206	-0.37	-0.00318	-0.36
Time spent in traffic jam (evening)	**-0.0168**	**-2.35**	**-0.0258**	**-2.20**
Resulting amount of time at work	0.000366	0.36	0.000624	0.41
Final-Loglikelihood	-796.306		-797.435	
Adjusted rho-square	0.173		0.172	

Based on these estimation results, the three different measures of accessibility can be computed by applying equations (1), (2) and (3) – only estimates reported in bold in Table 1 are used for

[7] Note that a Ben-Akiva & Swait (1986) test for nonnested models showed that the difference in fit was statistically significant at a 10%-level of significance.

simulation purposes[8]. To study how land use/transport strategies are appraised differently by the three different accessibility measures presented in this paper, the following hypothetical situation is constructed: A representative traveler faces a choice from the choice set as defined above. Time spent in traffic jams equals zero minutes (during both morning and evening commute) for the early and late departure times, and it equals 15 minutes (during the morning as well as the evening commute) for the regular departure time.

The focus is on a 'peak spreading' strategy that reduces time spent in traffic jams during the morning commute at the traveler's regular departure time, at the cost of increasing time spent in traffic jams during the morning commute at earlier and later departure times (both to an equal amount– however, we assume that the impact of the peak-spreading strategy on total off-peak congestion is smaller than the impact on peak-hour congestion, due to the likely existence of unused capacity during off-peak hours). Accessibility benefits of this strategy are computed as a function of the reduction in time spent in traffic jams during the morning commute. Formally, this implies the following settings, where *reduction* is varied from 0 to 15 minutes:

Jam(ea, mo) = Jam(la, mo) = reduction / 3; Jam(reg, mo) = 15 – reduction

Jam(ea, ev) = Jam(la, ev) = 0; Jam(reg, ev) = 15

Here, *ea* stands for 'early', *reg* stands for 'regular departure time' *la* stands for 'late', while *mo* stands for 'morning' and *ev* stands for 'evening'. Note that whithout peak spreading strategy (i.e., reduction = 0), the regular departure time is the most popular of the three. More specifically, it achieves a market share of 45% when a RUM-based decision model is assumed, and a share of 40% when a RRM-based decision model is used – the remaining two alternatives each get 50% of the remaining market share. Figure 2 shows results in terms of accessibility benefits as a function of the magnitude of the reduction in peak hour congestion; that is, it gives the expected utility of the choice set after the peak spreading strategy minus the expected utility of the choice set before the peak spreading strategy. Benefits computed by means of the

[8] More specifically, we re-estimated the models without the insignificant variables and used resulting estimates for simulation purposes. Differences with the parameter-values presented in Table 1 were very minor and are not reported here. Note that for this re-estimated model the RRM-model's fit (Final-LL of -797.3) was statistically superior when compared to the RUM-model's fit (Final-LL of -798.7) at a 5%-significance-level.

conventional Logsum are given by the solid line; those computed by means of the measure presented in equation 2 (assuming preference volatility) by the dashed line; those computed by means of the measure presented in equation 3 (assuming preference volatility and regret-based decision-making) by the dotted line.

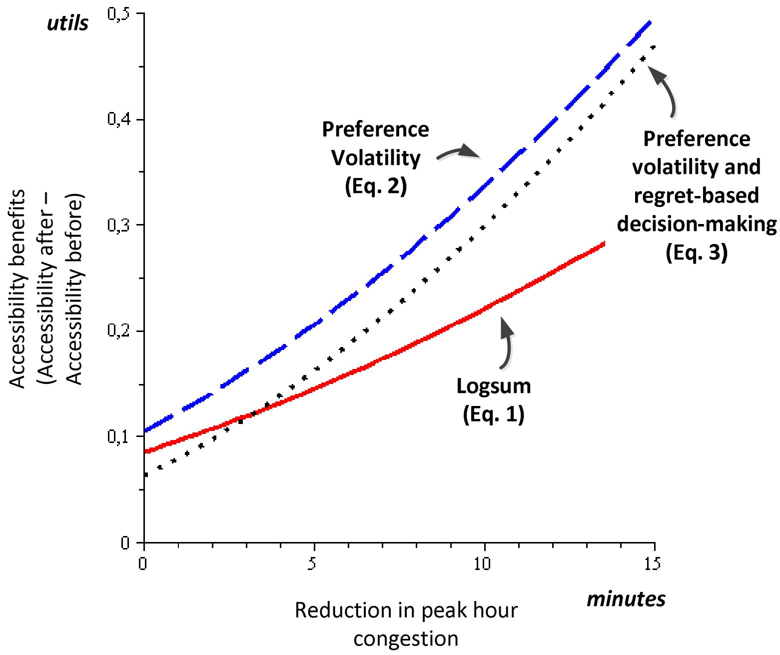

Figure 2: Accessibility benefits of a peak-spreading strategy[9]

A first thing that catches the eye is that the three measures imply rather substantial differences in computed accessibility-benefits. Especially the difference between the Logsum (solid line) on the one hand, and the other two measures (dashed and dotted lines) on the other hand, is non-negligeable as the latter two suggest around 60% higher benefits than the Logsum for reductions close to 15 minutes. It goes without saying that these numbers should by no means be treated as generic or absolute, since they are based on the specifics of our small-scale case study. As will be argued below, also the sign of the difference is specific to the settings of our example.

[9] Note that, since our sub-sample of the data did not contain a cost-related attribute, we are unable to measure accessibility-gains in monetary terms.

However, the example does show. However, they do signal that the alternatives to the conventional Logsum-approach may easily lead to different policy-implications: in the context of our example, a particular peak spreading strategy may achieve positive net benefits in the context of one accessibility-measure, while achieving negative net benefits in the context of another measure (depending on the costs associated with implementing the strategy).

A second observation is that both the two measures based on preference volatility (the dashed and dotted lines) appear to imply higher accessibility-benefits associated with reductions of time spent in traffic jams, than does the Logsum-measure which assumes stable preferences (the solid line). An explanation for this lies in the fact that reductions in peak hour congestion increase the popularity of the peak-hour alternative ('regular departure time'): it becomes by far the most popular alternative for large reductions (claiming a share of around 65%), while in the initial situation the peak hour-alternative is only marginally more popular than the two off-peak alternatives (claiming a share of 40-45%, depending on wether the RUM-based or RRM-based choice model is used). In the initial situation, where all three alternatives are more or less equally attractive, the two accessibility measures that assume volatile preferences predict that there is a relatively large probability that a chosen alternative (based on either decision-utility or decision-regret considerations) turns out to differ from the alternative with highest *experienced* utility. In other words, these measures predict that in the initial situation there is a large chance that a suboptimal choice is made. When the reduction in peak-hour congestion becomes more and more pronounced, the 'regular departure time' alternative becomes more and more popular relative to the other alternatives, and choosing a suboptimal alternative due to preference volatility becomes less and less likely. This move from a high towards a small probability of making a suboptimal choice implies additional accessibility gains that are captured by the two measures that assume volatile preferences, while being ignored by the conventional Logsum-measure which assumes that suboptimal choices are impossible since preferences are stable[10].

[10]This also implies that the accessibility-benefits estimated by a Logsum-measure, of a land use-transport policy which aims at increasing the popularity of a relatively unattractive alternative with the aim that the alternative becomes equally attractive as its alternatives, will be *higher* (ceteris paribus) than those estimated by its counterparts that assume volatile preferences.

A third observation that can be made, is that the accessibility-measure that assumes preference volatility and regret-based decision-making (dotted line) results in lower accessibility benefits than the accessibility-measure that assumes volatile preferences only (dashed line). The former measure (which assumes regret-based evaluation rules for decisions) even implies somewhat smaller benefits than the Logsum for small reductions in peak-hour congestion. The reason for this is that the RRM-model predicts a smaller probability for the 'regular departure time'-alternative than does its RUM-based counterpart[11]. This difference ranges from more than five percentage points in the initial situation to around one percentage point when a 15 minute reduction in peak-hour congestion is established. Since improving an alternative only leads to higher accessibility to the extent that the alternative is in fact likely to be chosen by the traveler, the logical result of this difference in popularity of the peak-hour is a difference in accessibility benefits in favor of the utility-based measure.

6. Conclusions

This paper argues that there is a discrepancy between what Logsum-measures of accessibility aim to measure (experienced utility) and what they actually measure (decision-utility). The former type of utility refers to the evaluation of a chosen alternative during or after execution, while the latter refers to the evaluation of an alternative during or right after the moment a choice

[11]The reason for this lies in the fact that the RRM-model assumes that regret is experienced with respect to all alternatives that perform better on a particular attribute. The result of this is that when an alternative performs worse than all other alternatives on a particular attribute, the RRM-model associates a relatively large penalty with this attribute-level inferiority as it adds together the regrets associated with comparing the alternative with each of the other alternatives (in terms of the given attribute). This is exactly what happens in our example, especially in the initial situation: the 'regular departure time'-alternative performs worse than both its competitors in terms of the attributes 'time spent in traffic jam' (morning and evening), and as a result it is heavily penalized by the RRM-model. Note that its large and positive constant makes that it is still the most popular alternative of the three alternatives. As the reduction in peak-hour congestion gets larger, the difference between shares predicted by RRM and RUM (and: the difference between the associated accessibility-measures) becomes smaller as the peak-hour alternative becomes less inferior on the attribute 'time spent in traffic jam' during the morning commute.

is made. We argue that accessibility should preferably be conceptualized and operationalized in terms of experienced utility, but that this type of utility is difficult to measure directly in a consistent manner. Motivated by these observations we show, taking the Logsum as a starting point, how its building blocks (parameters estimated from choice patterns) can be used to construct closed-form and easy to compute accessibility measures that provide an approximation of experienced utility.Based on discrete choice-models estimated on departure time-choice data, a small-cale and illustrative case study is presented. Numerical results are intuitive, and suggest that the different accessibility measures may imply different land use/transport strategies.

At least four avenues for further research readily come to mind. First, it appears worthwile to compare the three measures on other choice situations. Preferably, also larger scale case-studies should be performd, to get an idea of how the three measures compare when evaluating accessibility benefits at a more aggregated level (this paper's case study focused on accessibility benefits for one 'representative' traveler). Second, whereas in this paper we focused on the example of regret-based decision making as an alternative to utility-based choices, there are of course many other decision-rules that may be studied. Third, whereas we assumed that the entire data are generated by one decision-rule or another (in our paper: utility-based or regret-based), it makes sense to extend our approach towards the less restrictive assumption that while some choices may be generated by one decision-rule, others may be the result of a different rule. For example, recent work (Hess et al., 2011) has highlighted – using latent class-analyses – that a share of up to 40% regret-minimizers may exist in a sample where utility-based models provide the better overall fit with the data. Fourth, as suggested earlier it makes sense to hypothesize that the discrepancy between decision utility and experienced utility may decrease over time as a result of learning. It would be worth while to study how this behaviorally intuitive notion can be captured in our modeling approach, and to see if it indeed holds in real life. One way of modeling this learning effect might be to allow the variance of the random error to be a (decreasing) function of the level of experience. In principle, when enough observed heterogeneity exists in the data in terms of experience levels, its impact on the discrepancy between decision and experienced utility can be captured.

In terms of policy-implications, the developed alternatives for the conventional Logsum-approach may be used as so-called second-opinion models. Given that these alternatives are based on behavioral premises which are fairly different from those underlying Logsum-based analyses, the finding that a particular land use-transport policy results in an attractive benefit-cost-ratio under all alternatives may be considered a sign of its robustness.

To conclude: the aim of this paper was certainly not to argue that one of the developed alternative accessibility-measures is to be prefered over the Logsum-measure, which has shown its worth in several applications and theoretical exercices. Instead, our aim was to highlight behavioral assumptions underlying the Logsum-approach to accessibility measurement which are usually discussed only very implicitly (if at all) in academic literature, while not being undisputed. We argue that at least these assumptions (of stable preferences and utility-maximization based decision-making) should be treated more explicitly, and that relaxing them may be an effort worth while undertaking.

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