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The Stochastic Satisficing model: A bounded rationality discrete choice model

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ABSTRACT

The interest in individuals' non-strictly rational behaviour has permeated into discrete choice models pushed by several psychological theories. We analysed Satisficing Theory, which is particularly useful when decision makers have to face the cognitive burden of complex decisions. Three principles of the theory are discussed noting that the third, partial pay-off functions, has not been addressed in the literature. We implement the three principles mathematically obtaining a discrete choice model in which the decision maker chooses the first satisfactory alternative. The model formulation is analytically derived, as well as its properties. The Stochastic Satisficing model allows variable or constant marginal rates of substitution and enables the explicit characterization of non-compensatory behaviours. The model can also explain attribute saturation and non-attendance of high order needs when basic needs are not fulfilled. We analysed the model performance on synthetic data, showing that it is likely to be unbiased and consistent for relatively common samples sizes. When tested on real data, the model proves its flexibility to also adapt to constant marginal rates of substitution. We conclude that the model is a good characterization of Satisficing behaviour for simple datasets.

1. Introduction

Since psychologist first pointed the potential impact of bounded rationality on decision making (Simon, 1955), there has been a growing consensus that people's limited processing faculties may affect the way they make decisions (Conlisk, 2014). This way, the concept of bounded rationality has permeated several disciplines, such as behavioural economics (McCain, 2015) and choice modelling (Araña et al., 2008; Stüttgen et al., 2012).

Simon's work on Satisficing Theory (Simon, 1955, 1956), henceforth ST, provides the basis for the Satisficing choice heuristic. Even though Simon's work does not give a precise definition for this heuristic (Manski, 2017), it highlights what elements of 'rational' choice are highly implausible and what reasons could trigger a simpler behaviour by decision makers (DMs). Simon analysed three simplifying principles. First, he argues that any choice model requiring the inspection of all attributes and a comparison (or consideration) of all the alternatives, would be highly implausible in many practical applications; thus simple pay-off functions are expected.[1] Then, Simon argues that information gathering is costly due to cognitive and processing effort, suggesting a reservation value or acceptance threshold. Finally, the third principle explicitly recognizes that DMs may have trouble combining attributes of a different nature (e.g.

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[1] Simple pay-off function are for example, distinguishing between acceptable and unacceptable alternatives. Even though Simon (1955) does not restrict the pay-off functions to be binary, to our best knowledge, only binary pay-off functions have been implemented when modelling Satisficing behaviour.

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quality and cost) into a single figure of merit (e.g. utility). Thus, DMs actually consider only partial ordering pay-off functions.

Several of Simon's ideas have been applied into decision and search theory. For example, some studies implemented directly the cost of information (Gabaix et al., 2006). Other researchers have implemented indirectly the cost of information through sequential inspection of the choice set (Caplin et al., 2011; Manzini and Mariotti, 2014; Aguiar et al., 2016) or by analysing sequential menus (Papi, 2012). Several models considered a reservation utility in accordance to ST (Gabaix et al., 2006; Caplin and Dean, 2011; Papi, 2012). However, to the best of our knowledge, none of the referenced studies have applied the third principle of ST (i.e. partial ordering pay-off functions), probably because it implies dismissing the concept of utility.

Following these theoretical considerations, discrete choice models have attempted to implement the principles in different ways; however, most models have not incorporated important cornerstones of the theory.[2] While some applications of ST completely inspects all available alternatives –violating the second principle– (Recker and Golob, 1979; Young et al., 1983; Durbach, 2009), other applications mix attributes of a different nature into a single figure of merit, violating the third principle (e.g. Radner, 1975; Richardson, 1982; Araña et al., 2008). Only recently, ST has been thoroughly applied using eye-tracking technology (Stüttgen et al., 2012), yet, this is not possible in most choice settings. Therefore, despite several attempts to implement ST in practice, a Satisficing choice model that can be used broadly with simple data[3] does not exist.

The main contribution of our paper is the proposal of an econometric model, the Stochastic Satisficing model, that applies ST as rigorously as possible for a simple dataset.[4] To create this model, we start by describing a general Satisficing behaviour, which incorporates the three ST principles that could lead to several ST models. Then, simplifications are stated to adapt to the data structure and the econometric model is solved. As a result, the model considers that DMs choose the first alternative which is stochastically satisfactory on all dimensions of the pay-off vector. Thus, DMs are assumed to explore the choice set sequentially, in a process based on alternatives rather than on attributes (Williams and Ortuzar, 1982).

One of the key features of the Stochastic Satisficing model is the consideration of a multidimensional pay-off acceptability function. This approach, which is explicitly suggested by Simon (1955) and identified by us as the third principle, differentiates our model from previous work. By using this approach, we imprint further realism to the choice heuristic and do not restrict the model structure, which has scalar utility functions as a particular case. As the multiple dimensions of the pay-off function interacts into a single stochastic acceptability, different substitution patterns are analytically obtained.

We test the proposed model's properties on synthetic and real data. The analysis on synthetic data suggests that the model could be unbiased and that consistency is reached with common sample sizes. The real data case provides an example where the model is able to adapt its behaviour when the evidence in the data suggests that constant compensation among attributes does actually exist.

The rest of the paper is organised as follows. In section 2 we describe the ST principles and the reported evidence in the literature that motivates people using a Satisficing choice heuristic. In section 3, we propose a general Satisficing behaviour theory which is later simplified into the Stochastic Satisficing model. We end section 3 by analysing the analytical properties of the model. Then, section 4 analyses the model in two contexts: synthetic and real data. Finally, conclusions are presented in section 5.

2. On Simon's theory: principles and motivation

We first address the behavioural theory of rational choice proposed by Simon (1955, 1956) and discuss its main principles. Then, we analyse how context can induce a Satisficing choice heuristic.

2.1. Simon's theory principles

Most discrete choice models, such as Random Utility Maximization –RUM– (McFadden, 1973), Elimination By Aspects –EBA– (Tversky, 1972a, 1972b), and Random Regret Minimization –RRM– (Chorus, 2010) among others, require the evaluation of all alternatives, involving a large cognitive load for DMs. Furthermore, this burden is increased in RUM and RRM due to the consideration of all alternative attributes in compensatory trade-off terms of either utility or regret.

ST suggests several simplifications, or principles, that make the behavioural process more plausible for the human mind. We have categorized such simplifications into three main principles.

The first, states that DMs may assume only a few evaluation outcomes per alternative (e.g. acceptable or not; desirable, neutral, or undesirable) instead of a continuous outcome (e.g. utility). In the Stochastic Satisficing model, we postulate that an alternative can be either acceptable or non-acceptable.

The second principle is based on the fact that information gathering is not costless. People may use information sequentially while they acquire it and use only a subset of the available information. For example, neither the need to visit an apartment before deciding if it is acceptable, looking at a shelf of a supermarket before settling for a bottle of wine, nor examining the attributes of alternatives presented in a stated choice survey are free of cost or burden. The higher the information cost is –probably relative to the importance of the choice decision– the simpler the cognitive process may become (e.g. not inspecting all alternatives or attributes). Simplifications can be attained by inspecting a subset of attributes of each alternative, as in the EBA model, or by inspecting a subset of alternatives as in the Satisficing heuristic. Therefore, in the Stochastic Satisficing model we assume that people truly choose the first “good enough” alternative.

[2] This is probably because Satisficing has been interpreted in different ways among researchers, without reaching a consensus (Manski, 2017).

[3] By simple data, we understand only alternative profiles and the chosen alternative.

Finally, the third principle is associated with the difficulty that DMs may have in mixing attributes of a different nature (e.g. quality and cost). Contrary to this principle, in random utility modelling for example, the analyst assumes that DMs are willing to compensate attributes at certain marginal rates of substitution. ST suggests that DMs may not analyse such attributes conjointly, but rather consider them independently and still infer if the alternative is acceptable or not.

2.2. How context can induce satisficing

Several reasons why someone could choose using a Satisficing heuristic have been reported in the literature. Simon (1956) suggests that when the choice is too complex, people could use simpler heuristics to cope with a high cognitive burden. We think that if complexity is related to the size of the choice set, then Satisficing behaviour or any other heuristic based on alternative discarding is highly plausible. Conversely, if complexity is associated with the number of attributes, then EBA or any other choice heuristic based on attribute discarding may be expected. If complexity is not an issue, then utility maximization might be a plausible choice heuristic.

A second argument related to the propensity of using a Satisficing heuristic is that search costs could prevent people from inspecting the complete choice set (Simon, 1955). Indeed, maximizing utility considering search costs leads to a class of Satisficing behaviour (Richardson, 1982). Nevertheless, even if Satisficing is optimal under utility maximization with search costs, ST dismisses the concept of utility as being intractable for DMs (Manski, 2017). Finally, we postulate that costs may be interpreted not only as direct costs (e.g. monetary or time), but as indirect costs (e.g. effort) –a similar definition may be found in Chassang (2013)–. Under this interpretation, even the mere possibility of losing a quasi-unique good for not making the choice fast enough (e.g. in a dwelling or real-estate choice), could be a cost that triggers the Satisficing choice heuristic.

Finally, Simon (1956) also questions the idea that DMs could even try to optimize a decision or to maximize utility. We do not discuss this notion here, but rather concentrate on the formulation of a practical model under the assumption that a Satisficing heuristic is appropriate.

3. The Stochastic Satisficing model

We start by describing a general Satisficing behaviour in accordance to ST. Then, several simplifying assumptions are proposed to adapt the model to the type of data that we want to use. Then, upon that simplified behaviour, we propose and solve an econometric model. We end up this section by analysing the proposed model's analytical properties.

3.1. A general satisficing behaviour

A choice heuristic describes how DMs choose one alternative from a choice set. It starts by analysing how DMs face a choice set and ends by choosing an alternative. In this model, DMs face alternatives sequentially and choose the first satisfactory alternative. This simple choice heuristic is divided into four stages or components.

First, the DM start by analysing an alternative of the choice set. The starting alternative is chosen in accordance to a probability density function. Depending on the nature of the choice set, the way to approach each alternative may differ and, therefore, the probability of choosing such alternative first could vary. For example, a list of alternatives in a stated choice experiment may be read sequentially; while products in a shelf may be faced differently depending on their position. Thus, attributes related with the probability of inspecting a certain alternative first may need to be estimated (Stüttgen et al., 2012).

The second component is a transition probability between alternatives. Once an alternative is inspected, the probability of inspecting another one could be identical or could vary in terms of its attributes. For example, a product located low in a shelf may be harder to reach than another ‘better located’, reducing the former probability of inspection.

The third component is an acceptability function. Typically, the acceptability of an alternative has been modelled by means of a utility function, and the DM chooses an alternative if it surpasses a reservation utility (Richardson, 1982; Tyson, 2008; Caplin and Dean, 2011; Zhao and Huang, 2016). In spite of common practice, we model the acceptability function as a partial pay-off function or a vectorial function of acceptabilities in accordance with ST (Simon, 1955).[4] In our model, the acceptability of an alternative i (A_{iq}) evaluated by individual q is given by the acceptability of each component of the acceptability vector as stated in Equation (1).

$$\Pr\left(A_{iq} = 1\right) = \prod_{\forall\, k\, \in\, K} \Pr\left(a_{kiq} = 1\right) \tag{1}$$

Each element that impact the acceptability of an alternative may be interpreted as an attribute or combination of attributes. Attributes being compared in a compensatory way are evaluated in the same acceptability function, whereas attributes non-compensated are evaluated in different functions; further comments are addressed in section 3.4. Thus, modelling a utility function is a restricted case where every attribute is compared in the same acceptability function.

Finally, the last stage concerns the behaviour of DMs once an acceptable alternative is found. Theoretically, we state that the DM can continue searching alternatives with certain probability, which could even be decreasing while the search continues longer after

[4] Note that in ST, the acceptability function could be dynamic since the preferences are built in the choice process rather than being defined externally. However, we do not incorporate this element of the theory.

encountering the first acceptable alternative. Indeed, eye-tracking data (Stüttgen et al., 2012) suggests that once DMs find a satisfactory alternative they do not choose it immediately.

3.2. Simplifications to the general satisficing behaviour

The general Satisficing behaviour applies rigorously ST; however, it requires rich datasets to be estimated. We adapt the general Satisficing behaviour to formulate a model that may be used with simple datasets. The data we want to work with contains just a full profile of each available alternative and knowledge of which was the chosen alternative. Thus, we intend to create a model based on a path dependent heuristic with unknown search paths. To accomplish it, assumptions or simplifications are considered.

The first simplified element is the probability of starting with a particular alternative. Given that the search path is unknown, the starting alternative is also unknown. Then, it is not possible to model what factors affect the probability to start with a certain alternative. Thus, we assume that the first alternative is randomly chosen with equal probability.

The second simplified element is the transition probability between alternatives. It is not possible to estimate a probability function of transition since the inspected alternatives and search paths are unknown. Then, we consider an equal transition probability between all alternatives.

Finally, we simplify how long the search continues after finding the first acceptable alternative. Because the length of this search is unknown, it is not possible to estimate any stopping criteria. Therefore, we assume that DMs choose their first acceptable alternative.

With these three simplifications, which are summarised in Table 1, we intend to estimate a Satisficing behaviour model with simple data. Nevertheless, availability of richer data could allow us to relax some of these simplifications, and another model could be created.

3.3. The mathematical model

The mathematical model described in this section represents the simplified Satisficing behaviour proposed in section 3.2. In this model, DMs randomly inspect their choice sets and choose the first satisfactory alternative. We start by defining the criteria for satisfaction by linking the acceptability of an alternative to the acceptability of each attribute. Finally, our model ends by linking the acceptability of each alternative to the probability of choosing the alternative.

3.3.1. Alternative acceptability

Following the simplified Satisficing behaviour, the DMs chooses the first acceptable alternative. Following ST, an alternative is acceptable if all attributes are satisfactory. Let A_{iq} be the probability that alternative i is acceptable for DM q. Then, A_{iq} is the joint probability that each attribute of i is acceptable. If we assume that the acceptance of each attribute is independent, then the joint probability is given by the product of attribute acceptabilities (Equation (1)) as stated in section 3.1.

3.3.2. Attribute acceptability

The acceptability of an alternative is based on the acceptability of alternatives' attributes. To define attribute acceptability, let K be the set of attributes and k an element of it. Each individual q has a set of acceptability thresholds; let F' be that set and f' an element of it. Each threshold f' is associated with a certain attribute k. Without loss of generality, we assume that more of each attribute is desirable. Furthermore, we could also assume that thresholds f' are a function for each individual. An attribute could be a single trait of the alternative or a combination of several characteristics. We refer to the acceptability of an attribute, a_{kiq}, in terms of its quantity or level x_{kiq}, as in Equation (2).

$$a_{kiq} = \begin{cases} 1, & if\ x_{kiq} > f'_{kiq} \\ 0, & otherwise \end{cases} \tag{2}$$

The threshold (f') represents the aspirational level for the specific attribute; a similar definition can be found in the work of Radner (1975) and Stüttgen et al. (2012). This threshold function does not depend on the level of the attributes, but could be influenced by socio-demographic characteristics and experimental conditions. For example, people with lower income could be very sensitive to cost; whereas the wealthy could almost ignore this attribute and have a higher cost threshold. We do not analyse the origin of this aspirational level, but follow Simon (1956): "it has no problem of maximization" involved. Further, we will assume, as in the random utility framework, that there are elements that the researcher can observe, which we will denote by f, and others that the researcher cannot observe and will be captured by random disturbances, ε_{kiq} . We will further assume that ε_{kiq} has a logistic distribution with mean zero and variance σ^2_{kiq}. Then, the probability that an attribute is acceptable is given by Equation (3).

Table 1
Satisficing choice elements, data limitations and simplifications.

Element	Problem	Simplification
Probability of starting with a particular alternative	Initial alternative is unknown	Equal probability of starting for all alternatives
Transition probability	Choice path is unknown	Equal probability of inspecting each alternative that has not been inspected
Probability of choosing, conditional on having found an acceptable alternative	Number of alternatives after inspecting the acceptable one is unknown	The first satisfactory alternative is chosen immediately

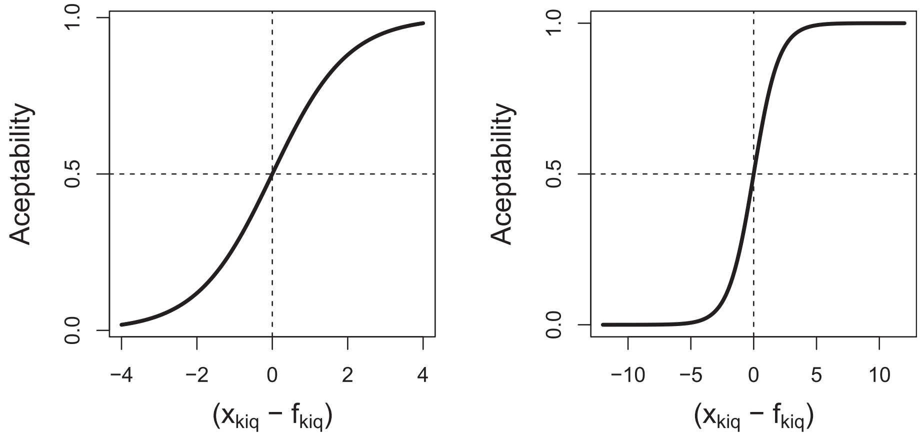

Fig. 1. Acceptability function versus different scale factors and attribute-threshold differences.

$$Pr(a_{kiq}=1) = Pr(x_{kiq} > f_{kiq} + \varepsilon_{kiq}) = Pr(x_{kiq} - f_{kiq} > \varepsilon_{kiq}) \tag{3}$$

Equation (3) is transformed into Equation (4) by using the expression for the cumulative probability function of the logistic distribution.

$$\Pr(a_{kiq}=1) = \frac{\exp(\lambda_{kiq}(x_{kiq}-f_{kiq}))}{1+\exp(\lambda_{kiq}(x_{kiq}-f_{kiq}))} \quad , \textit{with } \lambda = \frac{\pi}{\sigma\sqrt{3}} \tag{4}$$

Equation (4) is based on two terms, the scale factor and the threshold function; both are analysed in Fig. 1. The scale factor (λ_{kiq}) represents the impact of an additional unit of x_{kiq} in the probability of accepting attribute k; thus, higher values imply a higher sensitivity to changes in the attribute. On Fig. 1, the horizontal axis presents the difference between the attribute and its threshold. As the level of the desirable[5] attribute increases, higher is the probability of acceptance. The interpretation of the threshold function is two-fold. On the one hand, it indicates the point where attribute acceptability is 50%. Then, an increase in the threshold implies an increase in the point where acceptability reaches 50%. On the other hand, higher values of the threshold are related with a decrease in the difference $x_{kiq} - f_{kiq}$ or a decrease in the quantity that surpasses the threshold; hence, increasing a threshold implies a decrease in the probability of accepting the attribute.

3.3.3. *Alternative probability*

The link between the acceptability of an alternative and its probability is developed by using the assumptions made in section 3.2. Let t_{qi} determine the alternative chosen by the individual as in Equation (5).

$$t_{qi} = \begin{cases} 1, & \textit{if alternative } i \textit{ is chosen} \\ 0, & \textit{otherwise} \end{cases} \tag{5}$$

Because we only know the DMs choices but not their search paths, we assume that DMs choose the first satisfactory alternative. To link this assumption to the probability that alternative i is chosen by the DM, every possible path that ends in choosing alternative i must be computed. To avoid this calculation, we suppose that DMs could have separated their complete choice sets into two: a set of acceptable alternatives and another one of unacceptable alternatives. Note that these separated choice sets are designed as an artifice to solve the mathematical problem; indeed, DMs never split their choice sets.

Let I' be the set of acceptable alternatives and $|I'|$ its cardinality. If the search path is completely random, i.e. every alternative has the same probability of being analysed; then, the probability of choosing alternative i is the probability of inspect it before another alternative in I'. This probability is given by Equation (6).

$$\Pr(t_{qi}=1|I') = \frac{1}{|I'|} \tag{6}$$

Equation (6) is based on the DMs acceptable choice sets. The acceptable choice sets are based on the probability that each of its alternatives is acceptable. Let $\Pr(I')$ be the probability that only alternatives in I' are acceptable. Then, assuming that each alternative is analysed independently, the probability of choosing alternative i is given by the total probability over every conditional choice sets, shown in Equation (7).

[5] The attribute is desirable because the scale function is positive; further details are provided in section 3.4.

$$p_{qi} = \Pr(t_{qi} = 1) = \sum_{\forall I' \in I} \Pr(t_{qi} = 1|I')\Pr(I') = \sum_{\forall I' \in I} \frac{\Pr(I')}{|I'|} \tag{7}$$

Equation (7) establishes the link between the acceptability of an alternative, through the acceptable choice set, and the probability of choosing it. The only unknown element in Equation (7) is the acceptable choice set probability, which is explained as follows.

3.3.4. Acceptable choice set probability

The probability that subset I' exists, $\Pr(I')$, is built from its alternatives' acceptability. For example, if there are m acceptable alternatives and n non-acceptable ones, the probability that only the m alternatives in I' are acceptable is given by Equation (8).

$$\Pr(I') = \prod_{m \in I'} \Pr(A_{mq} = 1) \prod_{n \notin I'} \Pr(A_{nq} = 0) \tag{8}$$

3.3.5. Opt-out alternative

The only case that has not been defined yet is the probability of choosing no alternative (i.e. opting-out). If an opt-out option is available, as in many SC experiments, its probability is straightforward and is given by Equation (9).

$$\Pr(opt - out) = \prod_{\forall i \in I} \Pr(A_{iq} = 0) \tag{9}$$

3.3.6. Likelihood function

Given that every outcome has been analysed, it is possible to define the likelihood function. If p_{*q} is the probability assigned by the model to the chosen alternative, then, when the opt-out alternative is available, the log-likelihood of the model is given by Equation (10).

$$ll = \sum_{\forall q \in Q} \log(p_{*q}) \tag{10}$$

If there is no opt-out alternative (i.e. DMs are forced to choose) or if we have information only about the DMs that chose, the estimated probabilities must be adjusted to represent only this spectrum of DMs. We can estimate the conditional probability upon their choices as in Equation (11).

$$\Pr(alt\ i) = \Pr(alt\ i|choosing\ any\ alt) * \Pr(choosing\ any\ alt)$$

$$\Pr(t_{qi} = 1) = \Pr\left(t_{qi} = 1 \middle| \sum_i t_{qi} = 1\right)\Pr\left(\sum_i t_{qi} = 1\right)$$

$$p'_{qi} = \Pr\left(t_{qi} = 1 \middle| \sum_i t_{qi} = 1\right) = \frac{\Pr(t_{qi} = 1)}{\sum_j \Pr(t_{qi} = 1)} \tag{11}$$

And the estimated log-likelihood without an opt-out alternative is given by Equation (12).

$$ll = \sum_{\forall q \in Q} \log\left(p'_{*q}\right) \tag{12}$$

Finally, consider that if no opt-out alternative is available, then estimating absolute acceptability is meaningless since the possibility of not choosing any alternative does not exist. In such case, the model estimates a relative acceptability, rather than an absolute alternative acceptability.

3.4. Model properties

Now that the basic model has been formulated, we explore some of its analytical properties, relax some assumptions made in the process and explore the model's performance.

3.4.1. Identifiability

The identifiability of the acceptability functions depends whether there is an opt-out alternative or not. If there is one, every element of the acceptability function is identifiable. In that case, both the scale factor and threshold functions of each attribute plus an alternative specific constant can be estimated. If there is no opt-out option, the model can only estimate the relative difference in acceptability and one alternative specific constant must be fixed, as in classical discrete choice models.

For example, in the classic logit model the scale factor is unidentifiable from the utility function. In our model, the scale factor is identifiable in the two cases discussed above. The probability of an attribute being acceptable is given by Equation (4); in it, the expression in the exponential function can be decomposed as Equation (13).

$$\lambda_{kiq}\left(x_{kiq}-f_{kiq}\right)=\lambda_{kiq}x_{kiq}-\lambda_{kiq}f_{kiq} \tag{13}$$

Since by definition f_{kiq} does not depend on the attribute level, x_{kiq}, both f_{kiq} and the scale factor (λ_{kiq}) can be identified.

3.4.2. Working with non-desirable attributes

On section 3.3 we assumed that attributes were desirable. If an attribute is undesirable (e.g. cost), the probability function of acceptance – Equations (3) and (4) – switches to Equation (14).

$$P\left(a_{kiq}\right)=P\left(x_{kiq}<f_{kiq}+\varepsilon_{kiq}\right)=P\left(x_{kiq}-f_{kiq}<\varepsilon_{kiq}\right)$$

$$P\left(a_{kiq}\right)=\frac{\exp\left(-\lambda_{kiq}\left(x_{kiq}-f_{kiq}\right)\right)}{1+\exp\left(-\lambda_{kiq}\left(x_{kiq}-f_{kiq}\right)\right)} \tag{14}$$

Note that the difference between Equations (4) and (14) is that the scale factor –that is always positive– is preceded by a negative sign if the attribute is undesirable. As the scale factor sign can be estimated, it is not needed to define *a priori* if an attribute is desirable or not. Indeed, if λ_{kiq} is freely estimated, a positive result would imply that an attribute is desirable; while if it is negative, the attribute is undesirable. As in random utility models, the only problem is when the scale factor is 0, in which case the parameters cannot be identified. This could only happen if the variance of the error term is infinite, and thus the model would not suit the problem.

3.4.3. Use of categorical variables

A third analysis refers to the use of dummies or categorical variables. When using this type of variables there is no continuous threshold implied, just the presence or absence of the variable. Then, we could define the probability of accepting the presence of the characteristic as in Equation (15).

$$\Pr\left(a_{kiq}=1\right)=\frac{\exp\left(\lambda_{kiq}f_{kiq}\right)}{1+\exp\left(\lambda_{kiq}f_{kiq}\right)} \tag{15}$$

Given Equation (15), it can be deduced that the scale factor is not identifiable from f_{kiq} –the same happens in RUM models– and must be interpreted simultaneously or normalised, as usual to unity, as in Equation (16).

$$\Pr\left(a_{kiq}=1\right)=\frac{\exp\left(f_{kiq}\right)}{1+\exp\left(f_{kiq}\right)} \tag{16}$$

3.4.4. What happens if there are search costs?

Several authors have theoretically accounted for search costs (Richardson, 1982; Tyson, 2008; Caplin and Dean, 2011). In our framework, the total search cost cannot be incorporated explicitly since each attribute is treated independently. However, we can assume that there is a fraction of the costs that could be associated with each attribute (e.g. monetary costs associated with the cost variable); let c_k be that cost and γ_k its sensitivity. Following Richardson (1982), the search costs would imply that the probability of accepting an attribute is given by Equation (17).

$$Pr\left(a_{kiq}\right)=Pr\left(x_{kiq}>f_{kiq}+\gamma_k c_k+\varepsilon_{kiq}\right)=Pr\left(x_{kiq}-f_{kiq}-\gamma_k c_k>\varepsilon_{kiq}\right) \tag{17}$$

An increase in the search costs increases the probability of accepting an attribute, since continue searching induces additional costs. If we assume that the cost is constant at each step of the process and that the function f_{kiq} has an attribute specific constant, then the cost is not identifiable from the constant. Hence, if we use an acceptance function that has an attribute specific constant, it would incorporate implicitly the search cost. Therefore, the use of an attribute specific constant in each acceptability function is highly recommended.

3.4.5. Understanding the rate of substitution in the Stochastic Satisficing model

The Stochastic Satisficing model allows for two types of substitution patterns between attributes. The first type focuses on attributes modelled in the same acceptability function; whereas the second, targets attributes in different acceptability functions.

Note that in this model there is no utility function, so a marginal rate of substitution (MRS) over a utility function is not possible. However, a MRS over the acceptance function attends a similar purpose in the sense of allowing to study the trade-off that enables the probabilities to be constant. Still, any substitution pattern should not be used in cost-benefit analysis, since there is only a vague relationship with individual's welfare. Yet, the MRS over the acceptability functions are valuable because they enable us to understand the behaviour of the model given a change in the attributes.

The first analysis considers attributes modelled in the same acceptability function. As anticipated in section 3.1, considering attributes in the same acceptability function entails a direct compensation between them. Let C_k be the space of attributes to be compensated with attribute x_k and c an element of C_k. Equation (18) states the structure of the attribute of an acceptability function where direct compensation is allowed. As a result, the term x_{kiq} in Equation (4) is replaced by Equation (18) leading to Equation (19).

$$x_{kiq} + \sum_{\forall c \in C_k} \theta_c x_{ciq} \tag{18}$$

$$\Pr(a_{kiq} = 1) = \Pr\left(x_{kiq} + \sum_{\forall c \in C_k} \theta_c x_{ciq} - f_{kiq} > \varepsilon_{kiq} \right) \tag{19}$$

From Equation (18), it is straightforward to see that the rate of substitution between x_{ciq} and x_{kiq} in the whole data spectrum is θ_c. Sections 4.1 and 4.2 presents two examples of applications of this type of substitution patterns.

The second analysis considers the relationship between attributes in different acceptability functions. We suggest that attributes should be modelled in different acceptability functions if the degree of compensation is limited. Even though no direct compensation is possible, in Equation (1) an increase in the acceptability of one attribute could substitute for the loss in another one. Then, the Stochastic Satisficing model, at least in an analytical way, allows for a (weak) substitution of one attribute for another in the case of attributes of a different nature.

Let v_{kiq} be the difference of the current attribute from its threshold ($v_{kiq} = x_{kiq} - f_{kiq}$). Then, as shown in Appendix A, the marginal rate of substitution (MRS) between any two attributes in different acceptability function is given by Equation (20):

$$\mathrm{MRS}_{x1,x2} = \frac{\lambda_1(1 + \exp(\lambda_2 v_2))}{\lambda_2(1 + \exp(\lambda_1 v_1))} \tag{20}$$

We are interested in finding if an acceptable attribute can compensate for a non-acceptable one; that is, if a positive $\lambda_2 v_2$ can substitute a negative $\lambda_1 v_1$. Fig. 2 shows the indifference curves between two attributes of different acceptability functions; the MRS varies over the product of λ_i and v_i. Note that if $\lambda_i v_i = 0$ there is a 50% probability of accepting the attribute and for $\lambda_i v_i = -2$ there is a 12% acceptance probability.

Equation (15) suggests that the MRS is not constant over attribute levels. From Fig. 2 can be deduced that when both attributes have similar satisfaction levels, a substitution is reasonable since MRSs are close to one. However, in order to trade an unacceptable attribute ($\lambda_1 v_1$) for an acceptable one ($\lambda_2 v_2$), the high MRS suggests that many units of $\lambda_2 v_2$ must be traded for one unit of $\lambda_1 v_1$, which might be unfeasible. For example, 8.5 units of $\lambda_2 v_2$ at $+2$ must be traded to compensate the loss of one unit of $\lambda_1 v_1$ at -4; while the MRS of 15 is reached when $\lambda_2 v_2$ is $+2.65$. These results suggest that the DMs are willing to compensate when the satisfaction of attributes has similar levels; further, if one attribute is undesirable individuals will not be willing to trade-off.

Moreover, Equation (15) could represent another feature of human behaviour: when an attribute is satisfactory, a person might prefer to increase another non-satisfactory attribute rather than obtaining an increase in the satisfactory one. So, this model allows to analyse two phenomena: first, why people could focus on second order needs only after high order needs are fulfilled, and second, the issue of attribute non-attendance. For example, when buying a public transport ticket, low income people could be highly sensible to cost (cost is in the unacceptable spectrum) and thus, they would not accept to pay a higher price for additional comfort. Conversely, wealthier people feeling that cost is acceptable, would be prepared to pay for additional comfort since price is already in an acceptable level.

To sum up, the Stochastic Satisficing model enables to model attributes that can be compensated, weakly compensated or non-compensated at all. This feature could give the model the flexibility to interpret different contexts.

4. Application to data

In this section, we apply our model to test its properties with finite samples and in different behavioural conditions. First, we use synthetic data with the objective of analysing convergence to simulated parameters; later we apply the model to a real choice context.

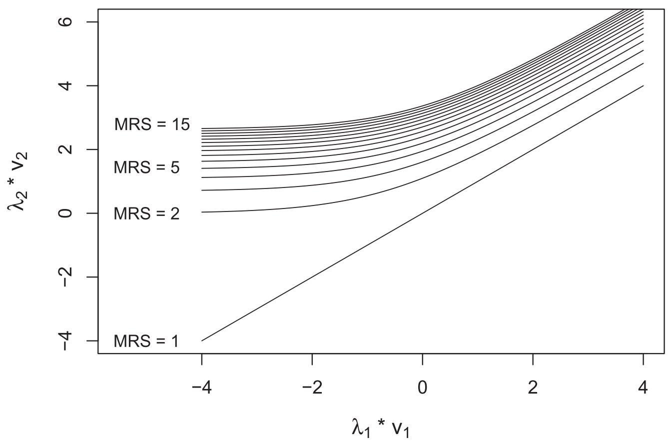

Fig. 2. Indifference curves of two attributes of different acceptability functions Marginal rates of substitution ranging between 1 and 15.

We use maximum likelihood estimation throughout.

In both experiments we use a well-tested real data bank (Ortuzar and Fernandez, 1985; Gaudry et al., 1989; Guevara, 2016; Guevara et al., 2016) about transport mode choice in Santiago de Chile. In the synthetic data case, we recreate a real scenario by randomly sampling choice sets; then, fictitious DMs choose from these choice sets. In the real case, we estimate the model using the real sample. The dataset considers journey-to-work trips made by 1374 individuals. As it contains only people who travel, there is no opt-out option. Individuals have between two and nine modes available. Each of these modes have the following attributes: cost, travel time, walking time and waiting time. Considering each available mode as an observation, their means and variances (expressed as the coefficient of variation for ease of inspection) are given in Table 2.

4.1. Application to synthetic data

It is well known that maximum likelihood estimates are consistent or asymptotically unbiased. However, we are interested in testing the model in finite samples sizes that are frequently reported in the literature. To test the approximate behaviour these finite samples we used synthetic data. The objective was to analyse the bias, the dispersion of the estimates, and possible identifiability issues. To test these elements, we analysed several sample sizes and different experiments within each sample size.

The synthetic experiment used a synthetic population based on the quasi-real dataset mentioned above. To create the databank, random observations (i.e. choice sets) were sampled from the real dataset. Then, simulated individuals chose using a Satisficing heuristic. No opt-out alternative was considered, so only individuals who choose are present in the data.

The simulated individuals searched for alternatives sequentially until they found a satisfactory one; then, this alternative was immediately chosen and the search finished. The synthetic population only considered cost, travel time and walking time. There was no compensation between cost and times, but there was compensation allowed between travel time and walking time. We also created a small preference for each alternative given by an alternative specific constant (ASC). The values of the parameters used to generate the simulated choices are shown in Table 3.

We analysed three sample sizes: 500, 1000 and 5000 observations; representing typical sample sizes that may be found in practice. To create the databank, we sampled random observations (i.e. sets of alternatives) from the real data set. For each sample size, 30 different and independent datasets were generated.

In Figs. 3–5, the boxplot presents the 25% quantile, the median, and the 75% quantile of the estimated parameters. Alternative specific constants are analysed in Appendix B. Additionally, the vertical line through the box, shows the minimum and maximum estimates for each parameter. We divided the estimated parameters by their target values to obtain a relative statistic easier to visualize. Finally, we plotted the mean estimate with a dot and, as a matter of reference, the unit value with a dashed line. Since every value is divided by the target value, estimates near the dashed line shows unbiased estimations. The difference between the mean point – mean of the 30 estimates – and the dashed line would show a systematic bias throughout the experiments.

The 1000 and 5000 observations' samples allow us to estimate the model with little variance throughout the 30 estimations. Interestingly, for every sample size the model tends to be unbiased in this particular dataset, since the points (mean estimates) are contiguous to the dashed line (target values). Moreover, model consistency has a desirable behaviour since the estimates tend toward their target values relatively fast as the sample grows.

To compare the difference in performance of having used a traditional discrete choice model, we also estimated a logit model for each experiment. The estimation results, shown in Table 4, indicate that ignoring the choice heuristic and simply using a RUM model would imply a statistically significant loss of likelihood.

As a conclusion of the synthetic experiment, testing the Stochastic Satisficing model with synthetic data indicates that it is an unbiased and consistent model when applied to frequently used sample sizes. When the nature of the data tends to be of a Satisficing

Table 2
Mean and coefficient of variation of the alternative attributes.

Attribute	Mean	Coefficient of variation
Cost (CLP$[a])	45.4	0.72
Travel time (min)	16.9	0.43
Walking time (min)	6.6	0.62
Waiting time (min)	1.5	0.97

[a] In 1985, 1 US dollar was worth CLP$ 160.

Table 3
Parameters used for simulation.

Parameter	Value	Parameter	Value
Cost sensitivity	−0.1	Cost threshold	45
Time sensitivity	−0.2	Time threshold	37
MRS travel – walking time	3.0	ASC1	1.6
ASC2	1.4	ASC3	1.2
ASC4	1.0	ASC5	0.8
ASC6	0.6	ASC7	0.4
ASC8	0.2	ASC9 (fixed)	0

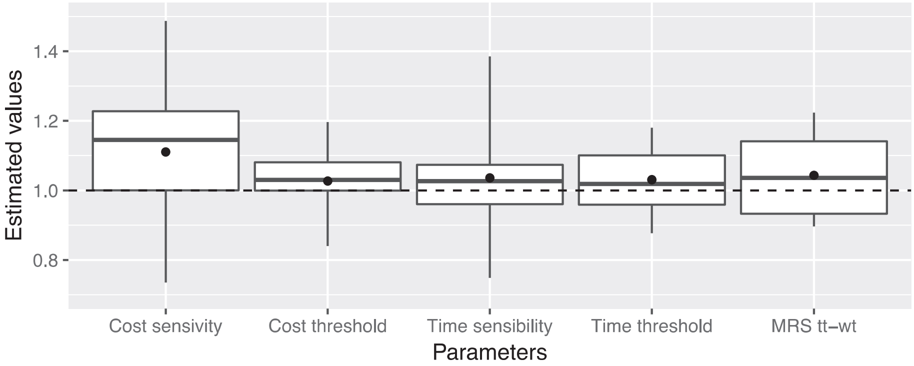

Fig. 3. Plot of estimated parameters relative to the targets in the 500 observations sample.

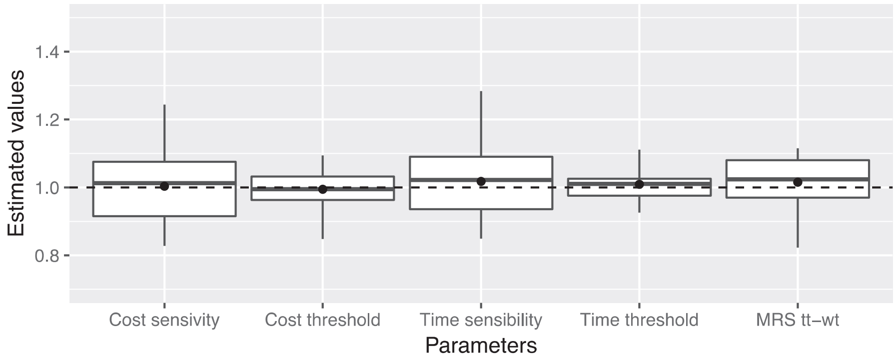

Fig. 4. Plot of estimated parameters relative to the targets in the 1000 observations sample.

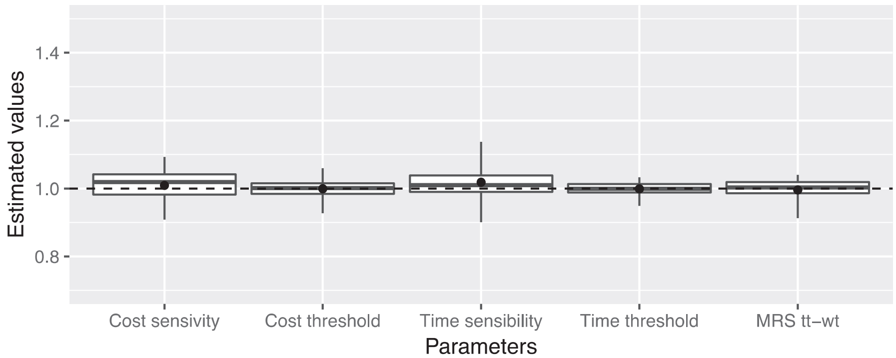

Fig. 5. Plot of estimated parameters relative to the targets in the 5000 observations sample.

nature, considering a RUM model could imply non-negligible loss of performance. Moreover, we expect higher differences when predicting with the RUM model if the attribute values change, as shown by Williams and Ortuzar (1982) in their pioneering response analysis work.

4.2. Application to real data

We estimated the proposed model using the real choices of the database. We modelled DMs choosing their transport mode depending on the cost, travel time, walking time and waiting time of each available alternative. All *times* were modelled using the same acceptability function, thus being able to compensate each other at a constant MRS –to be estimated– for the whole data spectrum.

Table 4
Satisficing and logit performance in the simulated experiment.

Mean log-likelihood(standard deviation)			
Sample size	Satisficing	Logit	Difference
500	−800 (17)	−845(18)	45
1000	−1617(23)	−1702(25)	85
5000	−8084(51)	−8503(51)	418

Table 5
Satisficing model estimation results for real data.

Parameter	Value (s. deviation)	Parameter	Value (s. deviation)
Cost sensitivity	−0.00474(1.00)	Cost threshold	−1850(10.61)
Time sensitivity	−0.0846(0.36)	Time threshold	−1670(5.77)
MRS travel – walking time	1.29(0.10)	MRS travel–waiting time	4.05(0.32)
ASC1	−3.32(0.09)	ASC2	−5.04(0.13)
ASC3	−4.63(0.14)	ASC4 (fixed)	0
ASC5	−2.54(0.07)	ASC6	−3.16(0.11)
ASC7	−4.02(0.16)	ASC8	−3.99(0.13)
ASC9	−3.59(0.12)		
Log-likelihood	−1609		
Sample size	1374		

Additionally, we estimated alternative specific constants (ASC). Table 5 presents the results of the estimates of the Stochastic Satisficing model using this dataset.[6]

The model results are reasonable. First, the signs of the sensitivities are both negative; meaning that the DMs do not like to pay more nor travel more. The marginal rates of substitution of travel time compared with walking time and waiting time have the expected signs and order of magnitude; furthermore, they are statistically different from unity at a 99% confidence level.

In this case, absolute acceptability cannot be obtained since an opt-out alternative is not available; thus, only relative acceptability can be analysed from this model. For example, the model indicates that if an alternative's cost is $CLP 40 (approximately 0.25 USD) and its cost is raised by 20%, then acceptability decreases by 4%.

MRS are an interesting output in this model; not because there is a welfare implication, but rather because it helps to interpret the behaviour of the model. The Stochastic Satisficing model is able to identify constant or flexible MRS.

We modelled times and cost in different acceptability functions. Walking and waiting times are both more onerous than in-vehicle time by 1.29 and 4.05 times respectively at an –imposed– constant rate. Even though we allowed for a flexible MRS of times and cost, in this sample the marginal rate of substitution is flat around 18 CLP$/min for the whole time and cost domains. This result provides evidence that, for this particular case, the logit assumption of constant marginal rates of substitution is probably reasonable. To test this hypothesis, we estimated a multinomial logit model with a utility function involving the same variables: cost, travel time, walking time, and waiting time. The results in Table 6 imply that the logit model outcome is reasonable with almost the same likelihood than the Stochastic Satisficing model.

The marginal rate of substitution between travel time and walking time is 1.4 and between travel time and waiting time is 4.3, which are similar to the Satisficing model. Similarities are also found in the case of the marginal rate of substitution between cost and time, being valued at 18 CLP$/min.

Note that although both models have similar flat MRS over the whole spectrum of data, this condition is imposed in the logit model rather than estimated as in the case of the Stochastic Satisficing model. Hence, the latter model is structurally more flexible.

Table 6
Random utility model estimation results for the real data.

Parameter	Value (s. deviation)	Parameter	Value (s. deviation)
Cost (×100)	−0.48 (0.17)	Travel time	−0.08(0.01)
Walking time	−0.11(0.01)	Waiting time	−0.34(0.05)
ASC1	−3.04(0.26)	ASC2	−4.75(0.25)
ASC3	−4.33(0.23)	ASC4 (fixed)	0
ASC5	−2.30(0.20)	ASC6	−2.89(0.21)
ASC7	−3.73(0.24)	ASC8	−3.69(0.20)
ASC9	−3.30(0.19)		
Log-likelihood	−1607		
Sample size	1374		

[6] We provide standard deviations rather than t-tests because a standard *t*-test with respect to zero is meaningless for the threshold attributes.

5. Conclusions

Starting from *Satisficing Theory* –ST– (Simon, 1955), we have analytically derived a behavioural choice model, where the probability that an alternative is accepted is equal to the joint probability of accepting each attribute. In the presence of an opt-out option, absolute acceptability is obtained, otherwise, only relative acceptability is possible.

Most model properties were also obtained analytically. We discussed identifiability issues and showed the link with the implicit search costs. An analysis of the MRS reveals that if attributes are analysed independently, they can only be compensated if they have a similar degree of acceptability. From this analysis, several features of human behaviour can be explained, such as attribute non-attendance because it is already highly acceptable, or valuing more an improvement of an inadequate level attribute that an acceptable one (*akin* to attribute saturation).

We tested the model properties with synthetic data, showing that the model seems unbiased and consistent. The model is able to estimate flexible MRS. When modelling with real data, the estimated parameters have the correct sign and magnitude, thus giving reasonable predictions. In this case a constant MRS (that has to be assumed in classical discrete choice models) was estimated for the whole data spectrum, demonstrating the flexibility of the Stochastic Satisficing model.

The main contribution of this model is the explicit characterization of non-compensatory behaviour as described in the literature. It explains why people could not be influenced by improving higher order attributes if basic ones are not fulfilled.

The model appears as an attractive alternative to traditional discrete choice compensatory models when decision makers find cognitive burden difficult to handle. It can capture extreme behaviour when one attribute is not compensated (e.g. cost for poor people or comfort for the well-off) and leave traditional models to work where they perform best, i.e. when individuals can compensate.

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Appendices.

Appendix A. Marginal rates of substitution for attributes of a different nature

To obtain the MRS for alternative acceptability, first we obtain the derivative of the acceptability function (Equation (1)). Let I^k be the space of all alternatives except k (i.e. $I^k = I - \{k\}$). Then the derivative of the acceptability function is given by Equation (21).

$$\frac{\partial \Pr(A_{iq}=1)}{\partial x_k} = \frac{\partial \Pr(a_{kiq}=1)\prod_{\forall j\in I^k}\Pr(a_{jiq}=1)}{\partial x_k}$$

$$\frac{\partial \Pr(A_{iq}=1)}{\partial x_k} = \frac{\lambda_{kiq}\exp(\lambda_{kiq}(x_{kiq}-f_{kiq}))}{[1+\exp(\lambda_{kiq}(x_{kiq}-f_{kiq}))]^2}\prod_{\forall j\in I^k}\Pr(a_{jiq}=1) \tag{21}$$

In this model the important issue is the amount by which the threshold is exceeded, let $v_{kiq} = x_{kiq} - f_{kiq}$ be that difference. The marginal rate of substitution is given by Equation (22).

$$MRSx_1x_2 = \frac{\dfrac{\partial \Pr(A_{iq}=1)}{\partial x_1}}{\dfrac{\partial \Pr(A_{iq}=1)}{\partial x_2}} = \frac{\dfrac{\lambda_1\exp(\lambda_1 v_1)}{(1+\exp(\lambda_1 v_1))^2}\prod_{\forall j_1\ \varepsilon\ I^1}P(a_{j_1})}{\dfrac{\lambda_2\exp(\lambda_2 v_2)}{(1+\exp(\lambda_2 v_2))^2}\prod_{\forall j_2\ \varepsilon\ I^2}P(a_{j_2})}$$

$$MRSx_1x_2 = \frac{\dfrac{\lambda_1\exp(\lambda_1 v_1)}{(1+\exp(\lambda_1 v_1))^2}\Pr(a_{2iq}=1)}{\dfrac{\lambda_2\exp(\lambda_2 v_2)}{(1+\exp(\lambda_2 v_2))^2}\Pr(a_{1iq}=1)} \tag{22}$$

$$MRSx_1x_2 = \frac{\dfrac{\lambda_1\exp(\lambda_1 v_1)}{(1+\exp(\lambda_1 v_1))^2}\dfrac{\exp(\lambda_2 v_2)}{(1+\exp(\lambda_2 v_2))}}{\dfrac{\lambda_2\exp(\lambda_2 v_2)}{(1+\exp(\lambda_2 v_2))^2}\dfrac{\exp(\lambda_1 v_1)}{(1+\exp(\lambda_1 v_1))}} = \frac{\dfrac{\lambda_1}{1+\exp(\lambda_1 v_1)}}{\dfrac{\lambda_2}{1+\exp(\lambda_2 v_2)}}$$

After rearranging the terms, this expression is identical to the stated in Equation (20).

Appendix B. Alternative specific constants' boxplot

As discussed in the synthetic data paragraph, the model is shown to be unbiased but with high variance for few observations. The alternative specific constant has a higher variance and is biased for the smaller sample sizes, overestimating the attribute as shown in Figs. 6 and 7. For higher number of observations, the model is unbiased and consistent as shown in Fig. 8.

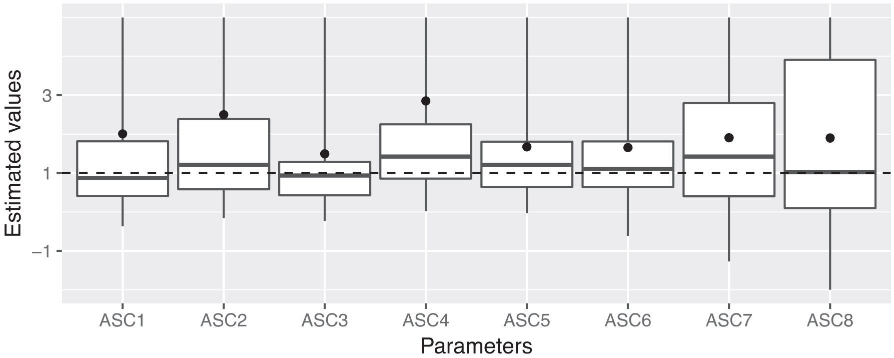

Fig. 6. Plot of the alternative specific constants relative to the targets in the 500 observations sample.

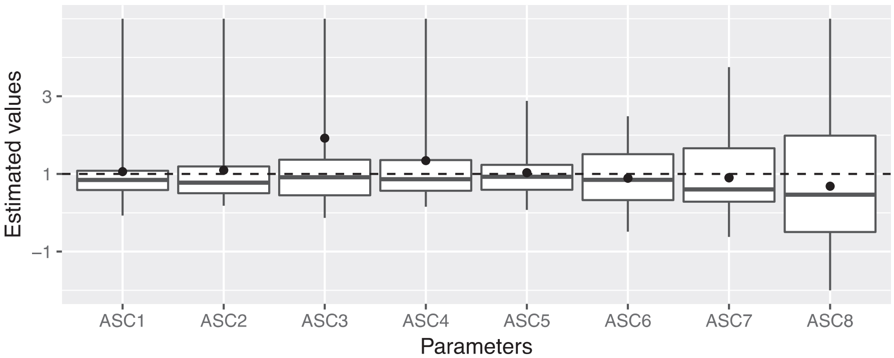

Fig. 7. Plot of the alternative specific constants relative to the targets in the 1000 observations sample.

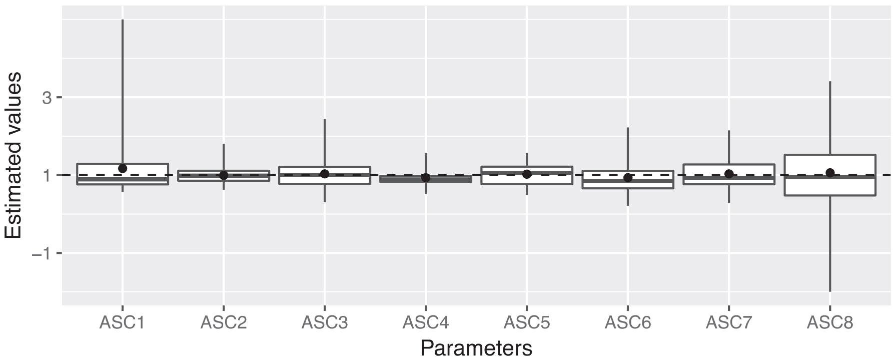

Fig. 8. Plot of the alternative specific constants relative to the targets in the 5000 observations sample.

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