INTERNATIONAL SCHOOL OF ECONOMICS AT TSU

ISET

MASTER THESIS

Status-quo Bias Explained Through the Framework of a Single Agent Choice Problem under Bounded Rationality

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Abstract. *In the first part of my research paper I set up a choice model which tries to explain status-quo bias. I try to explain the phenomenon by including sunk costs in a model where choice process is sequential i.e. agent chooses from the set of alternatives which are revealed to it sequentially. For this, I construct a choice procedure based on traditions of procedural rationality. Sunk costs enter the model through rational and behavioral channels. For example, through rational channel, sunk costs could be interpreted as means for revealing information about distribution of alternatives in a given population of elements and; through behavioral channel, sunk costs would affect decisions if we assume backward discounting of sunk costs (BDSC). BDSC is a new notion which I introduce and try to implement into the model. In the second part of the paper I will characterize the choice rule and reinterpret the traditional consistency conditions to fit the specific contextual characteristics of the choice procedure. In the last part, I model the procedure for finding optimal aspiration level replacing the assumption of bounded cognitive capabilities by the assumption that agent rationlly maximizes the objective function accounting for ex-post time and search costs i.e. agent intentionally chooses to become a satisficer rather than optimizer.*

1 Motivation and Literature Review

Super-rational homo-economicus that is able to maximize benefits using all the available information that environment reveals to it and using inerrable logic which is a priori given by the nature - this is the main paradigm of traditional economic theory on which it is built upon. The implicit fundamental assumption of this paradigm is that human beings are generally **able** to process as much information as nature reveals to them and that cognitive capabilities are such that they do not allow for mistakes in logic.

While this fundamental assumption diverges from realistic, one can also find justification for it by supporting the view that truth or wrongness of individual assumptions is not important rather, it should be the theory (system of ideas) which should be generating proper results (Boland, 1989). However, admitting this argument endangers the explanatory power of economics to give some plausible intuition behind real world phenomena.

As an illustrating example from evolutionary biology, Hamilton (1970) uses the concept of Nash Equilibrium to explain the behavior of frogs sitting around a lake endangered by a snake that randomly chooses location on the shore to jump out from the lake and catch a frog. Because frogs want to minimize the probability of being caught given other frogs' location on the shore, they aggregate in equilibrium. The model generates an equilibrium which is consistent with reality but do the frogs really play best strategies given others' strategies? Do they really understand that deviating from an aggregated cluster will increase their probability of being caught? Do their genes act as if they were playing according to rules prescribed by game theoretic reasoning thanks to some evolutionary forces? We never know.

Thus, while the result of a given model based on given assumptions might be consistent with reality, the explanation might be unconvincing or/and impossible to falsify.

1.1 Procedural Rationality

Economists have realized such problems with classical economic theory and have proposed various views about human behavior which are more realistic in a sense that they try to validate explanatory power of economics. Theory of Bounded Rationality (BRT) proposes a behavioral modification of traditional version of rationality assumption allowing for cognitive constraints of human beings in decision making processes (Simon, 1955). Simon's idea is based on the fact that human beings have limited capabilities for processing information which is expressed through their choice behavior. Agents make choices from predetermined lists of elements where each element is categorized by an agent as being satisfactory or unsatisfactory leading to a simpler utility function and simpler computational procedure for making choice. An agent (satisficer) is satisfied if it encounters alternative which generates utility value above certain threshold and unsatisfied otherwise. If satisfied, it will stop the search process and choose satisfactory element (Simon, 1955).

This was the first attempt in economics to substitute classical rationality by procedural rationality which tries to address the question about $h$ow decisions are made rather than $w$hat decisions are made. Kahneman (2003) and Kahneman & Thaler (2006) provide anecdotal and experimental examples which suggest that people most often base their decisions on heuristics and simple rules of thumbs which do not require much deliberate cognitive effort. They divide cognitive processes into two categories: intuitive judgment which is effortless, fast and expresses immediate preferences and; conscious reasoning which is slower and effortful. They claim that humans most often use intuitive judgment which might sometimes even turn out to be effective if it is based on past experience and learning.

The importance of how decisions are made was also addressed by Sen (1993), claiming that classical axiomatic characterization of choice functions, which imply internal consistency of choice (Sen's property alpha and beta), should not be seen as universal foundations to all possible choice functions because external objectives of a given choice behavior, dependent on a specific choice context, are no less important.

Several things that procedural rationality has to take into account were proposed by Simon (1978); for example, importance of short term memory and limited computational resources in human decision making processes which are major bounds to human rationality. Considering those bounds, Simon sees the modeling methods of cognitive psychology and artificial intelligence as relevant to modeling human choice processes in economics. One of the main characteristics of such modeling is sequential choice from lists. Salant (2011) characterizes general choice functions which choose from given lists using automation. The procedure is similar to Simon's satisficing procedure. Salant and Rubinstein (2006) propose several examples of choice procedures which can be implemented by choice functions satisfying certain conditions and consistency axioms. One of such choice rules assigns choice to lists from a set $X \times (1, 2, ..., N)$ where (x, k) is alternative x in k^{th} place. In this procedure, choice is order-dependent because agent has preferences defined over $X \times (1, 2, ..., N)$ instead of X. Another rule is satisficing choice with status-quo bias, implying that agent encounters alternatives in a sequence and replaces in its register (remembers) previous alternative by the new one if objective utility derived from the new alternative is more than the objective utility of previous alternative plus some bias utility of previous alternative.

Choice functions accounting for short term memory have also been characterized using the Memory Cells Model (MCM) (Salant, 2003). MCM assumes that agent cannot remember entire past. Agent has certain amount of memory cells where in each cell it can store information about one alternative which was previously encountered.

When all memory cells are full, agent activates a function which determines a rule by which newly encountered alternative replaces some previously encountered alternative.

Procedural Rationality has also rationalized choice functions which choose from the elements on which cyclical preferences are defined and thus, exhibit preference reversals, by introducing a concept of sequentially rationalizable choice function. Mariotti (2007) has characterized such choice functions which choose from the sets where preferences are determined by multiple criteria. Characterization of more general choice functions under procedural rationality was proposed by Salant and Rubinstein (2008) choice function chooses from every (A, f) where A is some subset of X (grand set of alternatives) and f is an element from F (set of frames) where F can include default alternatives, various orderings or set of natural numbers which can have various interpretations depending on the choice context.

1.2 Sunk Costs

Besides procedural rationality, another important development in behavioral economics is inclusion of sunk costs in agents decision problems. Many experiments (Arkes & Blumer 1985; Knox & Inxter, 1968; Arkes & Hutzel, 2000; Manez et al., 2009) have been conducted which suggest that agents inflate probability of success of a given endeavor once it has been initiated and costs have been sunk. Results suggest that people are overly optimistic about already made choices and even more they are willing to invest further in the endeavor even if it is unprofitable according to marginal comparison. This kind of behavior is called sunk cost fallacy or escalation of commitment which is best described by throwing good money after bad.

The issue of sunk cost fallacy is addressed from two dimensions in the literature:

first, there is a debate on what causes the phenomenon and; second, there is a discussion about the situations where sunk costs help individuals to make better decisions (taking into account sunk costs is rational) and situations where they cause bad outcomes (behavioral bias).

One of the most popular explanations of sunk cost fallacy is cognitive dissonance theory (Festinger et al., 1956). which holds that people are averse to having conflicting cognitions and once they initiate some endeavor they are inclined to sticking to the course even if it turns out that the course is not worth maintaining. This way they justify their previous actions. Cognitive dissonance as a reason to escalation of commitment has been questioned by several studies. Whyte (1986) conducted experiment where subjects had to make investment in an unprofitable project after some costs were sunk. The study found that even when subjects were not personally responsible for sunk costs they exhibited tendency to complete the project. This means that subjects did not have prior actions to justify but nevertheless they were affected by sunk costs.

The alternative explanation to sunk cost fallacy is related to Prospect Theory and loss aversion (Kahneman & Tversky, 1979). Loss Aversion is a purely behavioral phenomenon which bears the idea that losses are more powerful than gains i.e. given a fixed reference point, one dollar loss reduces utility by more than one dollar gain increases it. The effect of sunk cost is captured by the change of reference point. Simple example illustrates this effect: A person who has just lost 2000$ and faces a choice between two lotteries $(1000, 1)$ and $(2000, 1/2; 0, 1/2)$ codes the problem as $(-2000, 1/2)$ and (-1000) if he/she has not adapted to losses yet (Kahneman & Tversky, 1979).

Besides explaining sunk cost effects via purely behavioral lenses, some authors suggest that accounting for sunk costs is often a rational decision making of an agent. Mcaffe et al. (2007) propose several simple models where agents react to sunk-costs because of financial and time constraints, reputational concerns and information content. For example, in case of information content, higher sunk costs might imply that investor has gained more information about a project and probability that the project will be completed successfully increases. Thus, investor should take into account sunk costs not to underestimate probability of success.

More recent empirical and theoretical studies have encountered reverse phenomena indicating a de-escalation effect of sunk costs. Heath (1995) conducted several lab experiments where some subject were randomly assigned tasks which incorporated monetary payoffs and costs (easy to set mental budgets) and others were given tasks which incorporated non-monetary costs (time, psychological costs). Experiments found evidence for de-escalating behavior. Authors attribute de-escalating behavior to mental budgeting i.e. people set budgets and track the benefits and costs for a given project and switch to other project based on the breakeven of total costs and total benefits. Authors claim that mental budgeting cause de-escalation when we have monetary payoffs - expenditures/ benefits are easy to track and calculate. On the other hand, escalation occurs when costs and benefits are not easy to track and forecast.

Mnemonomics has provided alternative explanation to de-escalating behavior. In a sequential investment problem, assuming that agents have limited memory, high sunk costs will have escalating and de-escalating effects. On the one hand, high sunk costs give a signal to investor, in the following period, that expected gains from the project was high enough which justifies incurring even higher costs (escalation effect). On the other hand, if costs are positively correlated, high sunk costs signal that project will need high costs for successful completion and thus, expected profits will be lower (de-escalation effect). Net effect depends on which one of those two effects dominates (Baliga & Ely, 2009).

1.3 Status-quo Bias

One of the most important consequences of including sunk costs in decision processes is status-quo bias (sometimes referred as endowment effect) which is the case when willingness to pay for a given object is lower than willingness to accept, once the object is owned by an agent. Samuelson and Zeckhausers decision making experiments show that status quo bias is an important phenomenon in decision making process (1988). People tend to attach higher weight to their status quo choice and are reluctant to deviate from it.

Samuelson and Zeckhausers (1988) propose three possible explanations to this phenomenon: 1. Transition costs to other alternatives are greater than benefits (rational decision making); 2. People are loss averse which means that they attach more weight to losses and thus, under uncertainty, prefer to keep status quo (cognitive misperceptions) and; 3. Choices are affected by sunk costs/benefits and people are inclined to commit to already chosen alternative (psychological commitment).

Kahneman & Knetsch (1991) argue for the second explanation while Samuelson and Zeckhauser (1988) claim that loss aversion is consistent with status-quo bias but it cannot be seen as a necessary condition for the existence of status-quo bias. They make a simple case for this claim by conducting experiments which are not framed in terms of gains and losses (choice of car color, job choice problem); nevertheless they find significant evidence for status-quo bias.

1.4 Backward Discounted Sunk Costs

This is a new notion which I introduce. The idea is that agents prefer bad things happening to them as far as possible in the past and as far as possible in the future. For example, agent who is afraid of dentists would delay going to the dentistry and agent whose close relative passed away a week ago would feel the loss more intensively compared to the agent whose close relative passed away a year ago. Standing at time t, agent would rather incur costs as far as possible from t i.e. it cares (feels) about the costs less as the costs are incurred further away in the future or in the past. Now, once we introduce the notion of sunk costs in a sense that agent has not adapted to already incurred costs at the point of making subsequent decision (Kahneman & Tversky, 1979), the notion of backward discounting becomes relevant for the sunk costs. To illustrate this by an example, consider agent who has sunk 100$ of investment in a project and now is considering to spend another 100$ which gives revenue of 200$ and nothing with equal probabilities. It has to decide whether to play the lottery $(200, 1/2)$. There are three possible ways agent codes this problem:

1. Agents decision is not affected by sunk costs: $0 \gtreqqless 0$ it simply compares marginal payoff of not playing the lottery to playing it. Thus, agent is indifferent;
2. Affected by sunk costs but has no backward discounting: $-100-100 \gtreqqless -100-100$ it compares marginal payoffs but this time adds sunk costs on both sides (note that each side accounts for current and next period payoffs);
3. Affected by sunk costs and has backward discounting: $-100-100 \gtreqqless -k \cdot 100-100$, where $k < 1$ agent would prefer to invest another 100$. Here is a rather neat point to be made: note that agent has two actions in its action space - either to play the lottery or to stop the search process. If one assumes that agent

faces backward discounted sunk costs in each case then it will be indifferent between those two actions. However, if we assume that sunk costs are backward discounted only if agent takes an action then $-100 - 100 \gtreqless -k \cdot 100 - 100$ holds and agent prefers to play the lottery.

To see the possible scenario behind 3, one could think about a guy dating a girl which is a costly endeavor in a sense that one devotes time and energy to this process. Now, imagine this guy finds out that the girl is messing around with some other guy. This fact makes this guy unsatisficed. Now, if he goes around and starts dating another girl (plays a lottery) he will forget about all that pain and sunk costs (devoted time and energy) easily while if he stops the search process sunk costs will be faded into the past memories more slowly. Because the guy realizes this he will be biased towards continuing the search process.

2 Research Question and Theoretical framework

In the first part of the paper I will link the notions of procedural rationality, sunk costs and status quo bias through a framework of a single agent choice problem under bounded rationality. Following existing tradition in the literature on procedural rationality, I make the following basic assumptions:

- Agent can not specify its preferences over all possible alternatives;
- Agent has limits on conducting complex computations;
- Agent is not far sighted;
- Alternatives are evaluated sequentially;

- Sunk costs enter the model through two channels: 1^{st} channel: rational channel (for example, following Mcafee et al. (2010)); 2^{nd} channel: behavioral channel - backward discounted sunk costs.

2.1 Simple Sample Model with Some Preliminary Implications

There exists a ground set Z of alternatives in the nature. Agent has a priori formulated criteria for satisfactory elements vs unsatisfactory ones. Define a partition of Z in two subsets X, Y where $X \subset Z$ is a set of unsatisfactory alternatives and $Y = X^c$ is a set of satisfactory alternatives according to agents criteria and $Y \neq \emptyset$. Z is partitioned according to some aspiration level χ.

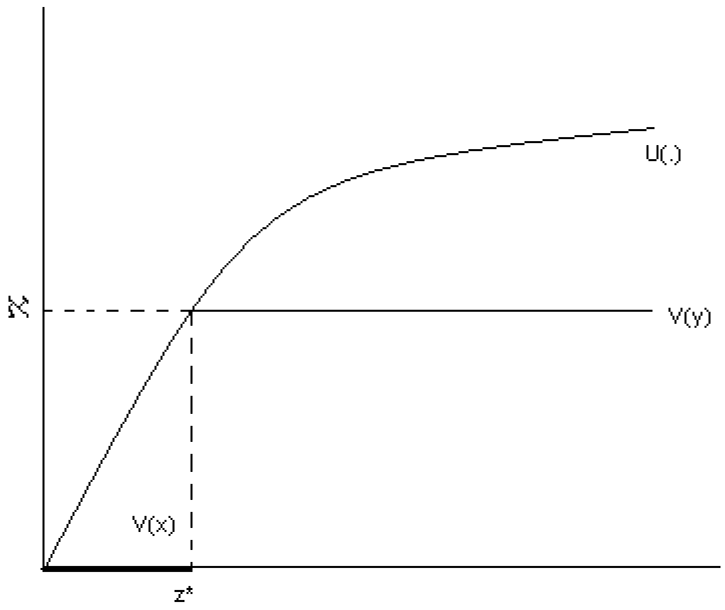
We assume that there exists a well defined utility function $U(z)$, defined over the alternatives from Z, which represents agents preferences over all alternatives. There exists some alternative z^* such that $U\left(z^*\right) = \chi$ and $\forall x U\left(x\right) < \chi$ and $\forall y U\left(y\right) \geqslant \chi$ then, χ is called an aspiration level implying, $y \succeq x$ $\forall x \in X$ and $\forall$ $y \in Y$, by aspiration rule.

Preferences are complete over $X \bigcup Y$. Thus, there exists $V : X \bigcup Y \rightarrow R$ that can be represented as a legitimate utility function. Assume the following simple binary utility function:

$$V\left(z\right) = \begin{cases} 0, if\ z \in X \\ 1, if\ z \in Y \end{cases} \tag{1}$$

Agent is Herbert Simons satisficer. It chooses alternatives from lists. List A is a

Figure 1:



finite sequence of elements from Z. I assume that a given element can not appear more than once in a given list.

Theorem 1. Since $Y \neq \emptyset$ then, given that agent starts a choice process, every possible realization of list will include exactly one satisficing alternative. (the proof will directly follow from the model's implications, below).

Choice process is sequential. Choice State at stage i is defined as a mental and actual state of an agent at the end of the stage i when it has already acquired information about a given alternative x (spending time, energy and money - agent has costs associated with gathering and processing information) and is on the point of making a decision to stick to the alternative or to continue the search process.

Agent has prior belief p_0 about the distribution of satisfactory alternatives in the population. It updates p_0 according to Bayes law as it gains more experience and knowledge throughout the search process. Updating p_0 is modeled following Mcafee and Mialon (2010). Main idea is that more costs agent incurs more information and experience it gains and p increases. Agent is uncertain about the total costs it will need to incur in order to find satisficing alternative. Total cost $\bar{C}$, needed to find satisficing alternative, is distributed according to cumulative $F(\bar{C})$. Using Bayes Law

$$p_1 = P\left(\bar{C} < C_1 + C_2 | \bar{C} > C_1\right) = P\left(\bar{C} < C_1 + C_2 \bigcap \bar{C} > C_1\right) / P\left(\bar{C} > C_1\right) =$$

$$= \left(F\left(C_1 + C_2\right) - F\left(C_1\right)\right) / \left(1 - F\left(C_1\right)\right) \tag{2}$$

$$p_n = \left(F\left(\sum_1^n C_i\right) - F\left(\sum_1^{n-1} C_i\right)\right) / \left(1 - \left(\sum_1^{n-1} C_i\right)\right) \tag{3}$$

This is a hazard rate which I assume to be increasing in C_i for $\forall i \in N$. With no loss of generality, for simplicity and complying with the assumption that hazard rate is increasing in C_i for $\forall i \in N$, we may assume uniform distribution of $\bar{C}$ where the least upper bound $\bar{C}$ is known by the agent (maximum cost that will guarantee that agent finds satisficing alternative with $p = 1$). Thus, p_n will become:

$$p_n = C_n / \left(\bar{C} - \sum_1^{n-1} C_i\right) \tag{4}$$

Taking into account sunk costs through this channel is a rational decision of an agent. Another channel through which sunk costs are taken into account is irrational (behavioral bias) and it can be attributed to the assumption that agent has a backward discounting of sunk costs. To see how this idea is realized in the model, say agent is in the choice state at stage 1 where it is unsatisficed and makes the following comparison:

$$0 - C_1 \gtreqqless -C_1^s + p_1 V(y) + (1 - p_1) V(x) - C_2 \tag{5}$$

Assuming that discount rate is $1, 0 - C_1$ is a net benefit at a current stage from unsatisficing alternative and $-C_1^s + p_1 V(y) + (1 - p_1) V(x) - C_2$ is expected net benefit from the stage 2 alternative. p_1 is updated prior, p_0, at stage 1; C_1 is expected costs (spending time, energy and money) of experiencing and gaining information on the next stage alternative; C_1^s is backward discounted sunk cost. When comparing right and left hand sides of the expression (5), C_1 and C_1^s do not cancel each other unlike the case when agent does not have behavioral bias attributed to backward discounting of sunk costs. Thus, at the stage 1 agent knows that it will care less about stage 1 costs at stage 2. Assume, $C_i \geq C_i^s \geq C_i^{2s} \geq C_i^{3s} \geq ... \geq C_i^{ns}$ for $\forall i \in N$.

Expression (5) simplifies to:

$$-C_1 \gtreqqless -C_1^s + p_1 - C_2 \tag{6}$$

At stage n:

$$-\sum_1^n C_i^{(n-i)s} \gtreqqless \sum_1^n C_i^{(n+1-i)s} + p_n - C_{n+1} \tag{7}$$

Note: we assume that agent stops a search process once it encounters a satisficing alternative because it can do no better (by definition it is a satisficer which means that once satisficed the process stops). Given that agent is unsatisficed at stage n, it will continue search process iff:

$$-\textstyle\sum_1^n C_i^{(n-i)s} < \sum_1^n C_i^{(n+1-i)s} + p_n - C_{n+1}$$

Or $p_n > \sum_1^n C_i^{(n+1-i)s} - C_i^{(n-i)s} + C_{n+1}$. Substituting (4) into (6):

$$C_n / \left(\bar{C} - \sum_1^{n-1} C_i \right) \geq \sum_1^n \left(C_i^{(n+1-i)s} - C_i^{(n-i)s} \right) + C_{n+1} \tag{8}$$

Expression (8) implies that acquired experience and information should be high enough to give incentive to the agent to continue the search process. Also, (8) suggests several interesting links between sunk costs and status quo bias. First,

$$\frac{\partial \left[\frac{C_n}{\bar{C} - \sum_1^{n-1} C_i} \right]}{\partial C_i} = C_n / \left(\bar{C} - \sum_1^{n-1} C_i \right)^2 > 0 \tag{9}$$

This means that sunk costs which enter the decision process through rational channel work against status quo bias.

Second,

$$\sum_1^n \left(C_i^{(n+1-i)s} - C_i^{(n-i)s} \right) < 0 \tag{10}$$

Sunk costs which enter the decision process through behavioral channel also work against status quo bias. The first part of the intuition is that the more past costs an agent has incurred, the more experience it has gained and the more likely it is to find a satisficing alternative which motivates agent to continue the search process rather than to stick to the unsatisficing alternative. The second part of the intuition follows from the assumption of backward discounted sunk costs. Agent knows that sunk costs will be *felt* less in the following stage as compared to current stage which also motivates it to continue the search process. It knows that in the next stage it will give less weight to the sunk costs from each previous stages. The only thing that works in favor of status-quo bias is C_{n+1}. If expected cost of the following stage is too high such that $C_n / \left(\bar{C} - \sum_1^{n-1} C_i \right) - \sum_1^n \left(C_i^{(n+1-i)s} - C_i^{(n-i)s} \right) < C_{n+1}$ then agent would prefer to stick to the existing unsatisfactory alternative. Thus, status quo bias is caused by purely rational decision making channel (transition costs are higher than benefits and thus, it is rational to stick to the existing alternative), while sunk costs indeed explain negative status quo bias.

2.2 Characterization of the Choice Rule

For characterizing the choice rule the reformulation of traditional choice consistency axioms is needed. For example Sen (1993) claims that axioms which guarantee consistency of choices from different subsets should be fully justified by the choice rule we explicitly define. This means that axioms behind the traditional preference optimization are not necessarily unique ones i.e. they should not be considered as basis of all possible choice behaviors. This argument gives us a right to redefine existing axioms to fit a given choice rule such that consistency of choices from different subsets is satisfied. For our choice model we should consider two important preliminaries before characterizing the choice rule: first, the choice rule will be based on our specific model in a sense that the set Z of alternatives will be reduced to X (set of satisfactory alternatives) and choice rule will be defined over these alternatives. The justification for this speculation directly follows from our models implication that agent never chooses unsatisficing alternatives and thus only satisficing alternatives are chosen from any subset. The exception would be if and only if $C_n/\left(\bar{C}-\sum_1^{n-1} C_i\right)-\sum_1^n\left(C_i^{(n+1-i)s}-C_i^{(n-i)s}\right)<C_{n+1}$ was satisfied for some choice stage n. Conditional on assuming that such exception does not occur (and this would surely hold if we assume that C is constant or decreasing with respect to n and since $p_0>C_1$ must always hold for an agent to start a choice process then the requirement of no exception is trivially satisfied)it is reasonable to define the domain of the choice rule as the set of satisfactory alternatives X. This also guarantees that for all $A \subseteq X, D\left(A\right) \neq \emptyset$, where $D(A)$ is a choice rule. Following Salants (Procedural

Analysys of Choice Rules 2011) definition of undecided-lists, $A \subseteq X, D(A) \neq \emptyset$, is equivalent to saying that according to $D(A)$ all lists are decided i.e. agent is always certain about its choice. However, note that all the properties of the choice rule are valid conditional on the implications of my model. Second, the choice function violates Order Invariance. If it did not, then the axioms for our choice rule would be similar to axioms for preference maximizing choice rules. Thus, we have the following characteristics, so far: domain consisting of only satisficing alternatives in which actual choice made is totally dependent on the order of alternatives (alternative in the first place will always be chosen); nonempty set of $D(A)$ for any given subset of alternatives. Thus, we know how the choice is being made by our agent according to the model and now we are only concerned about what it chooses.

Definition 1. *We say that a choice rule D satisfies Order Invariance if and only if* $D(x_1, x_2, ..., x_k) = D(xt(1), xt(2), ..., xt(k))$ *for* $\forall$ $(xt(1), xt(2), ..., xt(k))$ *and for* $\forall$ *permutations t of* $(1, 2, ..., k)$

The choice function can be explicitly written as:

$$D(A) = min_k \left(x_k | x \in A \; and \; x \succeq z^*; where \; U(z^*) = \chi\right)$$

or more simply $D(A) = min_k (x_k | x \in A)$, since the definition of A already satisfies $x \succeq z^*$ where $U(p) = \chi$ Thus, the rule simply says that because agent is satisficer, it is indifferent between all alternatives from any A and the actual choice only depends on whether a given alternative randomly turns out to be on the first place in the list. Denote $n(A)$ a cardinality of set A and $p(D(A) = x)$ a probability of choosing alternative x from the set A.

Axiom 1: For all $x \in S \subseteq T \subseteq X$ if $p(D(T) = x) = 1/k$ and $p(D(S) = x) = 1/k'$

then $1/k' \geq 1/k$, where $k = n(T)$ and $k' = n(S)$

Note that Axiom 1 is a modified version of Sens property α which simply states that whenever x has some chances of being a champion of the world then it must have at least the same chance of being a champion in its own neighborhood. The intuition is the same as the intuition behind Sens property α. The difference is that now we are talking about chances of being a champion instead of actually being a champion which is of course a consequence of the fact that our choice rule does not satisfy Order Invariance.

D satisfies **Axiom 1**.

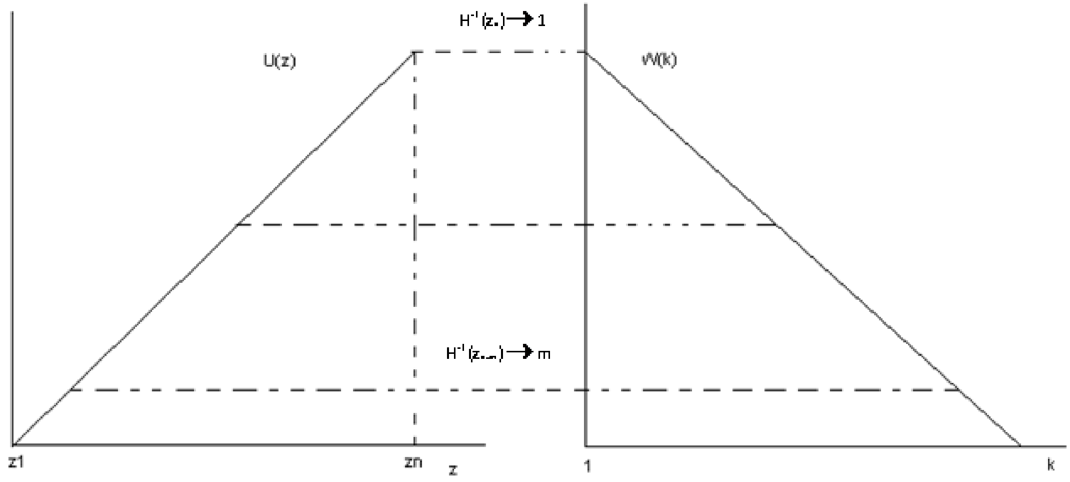
Proof. We use proof by contraposition. Assume $1/k > 1/k'$ for some $x \in S \subseteq T$ then it cannot be that we choose the first drawn satisficing element from A by our rule D. Now, suppose we always choose first element, then this implies that whenever $x \in S \subseteq T$, $p(D(T) = x) = 1/k$ and $p(D(S) = x) = 1/k'$ where $1/k' > 1/k$ i.e. $n(T) \geq n(S)$ but this is a contradiction. $\square$

On the other hand, we can show with the similar method that D is not a unique choice rule that satisfies Axiom 1; take for example $D\left(A\right) = max_k\left(x_k | x \in A\right)$. Another way to see how Axiom 1 is relevant is to observe how it modifies IIA principle for our choice rule. Indeed, Axiom 1 guarantees that whenever alternatives are added or subtracted to a given set then it cannot be that existing alternatives become unsatisficing for the agent or equivalently, for any $x \in S \subseteq T$ whenever $p(D(T) = x) = 1/k$ then it cannot be the case that $p(D(S) = x) = 0$. Thus axiom 1 ensures that no preference reversals take place.

2.3 Possible Extensions

One of the possible extensions to the model would be to find optimal aspiration level. I assume that agent knows the cardinality of set Z (denote by n) and it has to choose subset X s.t. $U\left(z^{*}\right) = \chi > U\left(x\right)$ for all $x \in X$. Thus, agents problem is to find optimal z^{*} from Z. Because agent has well defined preferences over alternatives in Z and these preferences are represented by $U(.)$, we find optimal k (denote cardinality of X by k) where $H : k \rightarrow Z$ is a bijection map from natural numbers to set Z where $H(1) = z_n$-where z_n is the first most preferred alternative by $U(.)$, $H(2) = z_{n-1}$ where z_{n-1} is the second most preferred and so on. We call this new utility function $W(k)$ (see fig 1). According to my model, agent always chooses satisfactory alternative. However, real utility $U(.)$ from a chosen alternative would depend on the choice of aspiration level. For example, agent could choose a very high aspiration level where $k = 1$ and it would be guaranteed that in some choice stage it would encounter such alternative. In this case, agent would be a maximizer. However, it would also be more likely that choice process would require more stages to draw that alternative. I assume that agent would

Figure 2:



prefer to choose as soon as possible because choice states are costly. Thus, there is a trade-off. High aspiration level would guarantee better alternative to be chosen but it would also take more stages and thus would be more costly. I assume that before agent starts search process it decides on the z_* from the set Z which would maximize its expected utility $E(W(k))$ from the chosen alternative (according to our satisficing procedure). Agent also has expected cost of search $T(k)$ which satisfies $T(k) < 0$. This function implies that if agent chooses lower aspiration level (higher k, which means that it is ready to stay satisficed with less preferred alternatives also), then it is expected that satisficing alternative will be encountered sooner in the search process and thus it will need less stages to find the satisficing alternative. Thus, agents problem becomes following:

$$ArgMax_k \left[\frac{1}{k}\int_1^k W\left(k\right)dk - T\left(k\right)\right] \tag{11}$$

Note that for a given k, the probability that a given x will be encountered from X is $1/k$ and thus, $\frac{1}{k}\int_1^k W\left(k\right)dk$ is expected utility. The general solution to 1 is given by:

$$-\frac{1}{k^2}\int_1^k W\left(k\right)dk + \frac{W\left(k\right)}{k} - T'\left(k\right) = 0 \tag{12}$$

To see some implications of this problem assume specific functional forms for $T(k)$ and $W(k)$. $T(k) = 1/ak$ and $W(k) = C - bk$ Solution gives:

$$k^* = \left(\frac{2\left(1 + a\left(C - b\right)\right)}{ab}\right)^{\frac{1}{2}} \tag{13}$$

In order to see how k depends on b and a:

$$k^{*\prime}\left(a\right) = \frac{\left(C-b\right)ab - 2b\left(a\left(C-b\right)+1\right)}{2\left(ba\right)^2}\left(\frac{ab}{2\left(1+a\left(C-b\right)\right)}\right)^{1/2} < 0 \tag{14}$$

$$k^{*\prime}\left(b\right) = \frac{-\left(2a^2b + 2a\left(1+a\left(C-b\right)\right)\right)}{2\left(ab\right)^2}\left(\frac{ab}{2\left(1+a\left(C-b\right)\right)}\right)^{1/2} < 0 \tag{15}$$

(14) implies that if expected costs for all k are lower, then agent chooses higher aspiration level and it becomes more likely that it will get higher utility alternative from satisficing search procedure. (15) implies that if utility of all given alternatives relative to less preferred alternatives goes up then agent chooses higher aspiration level i.e. if preferred alternatives become more preferred then agent will not accept in set X some low level alternatives which it accepted before.

3 Conclusion

Traditional economic theory has been concerned with analyzing economic phenomena using the models where agents are super rational homo-economicus. Behavioral economics has questioned this paradigm by proposing at least two important deviations from the trend: BRT and claim that sunk costs matter. I take some existing assumptions and model building methods from traditional BRT approaches, add sunk costs through rational and behavioral channels, assuming backward discounted sunk costs, and build a model which explains status quo bias via rational and behavioral channels. As an extension to the model, I propose a method for finding optimal aspiration level with an objective to further endogenise the process into the model.

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