Satisficing in Portfolio Selection*

- Theoretical Aspects and Experimental Tests –

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Abstract

The satisficing approach with its three constituent processes, aspiration formation, satisficing, and aspiration adjustment, is formally elaborated for a specific class of portfolio selection tasks. It is partly poorly confirmed by experimental data, indicating that bounded rationality requires teaching or, respectively, consulting, and learning. It is also discussed and tested experimentally whether satisficing is task transcending (are there individual constants in satisficing behavior for related tasks?) and absorbable (do we stick to satisficing behavior when becoming aware of it?).

* This is a summary paper, based on previous experimental studies. I thank my coauthors Gerlinde Fellner, Vittoria Levati, Boris Maciejovsky, Ev Martin, and Matteo Ploner for their cooperation.

Introduction

The most influential idea in the theory of bounded rationality is the satisficing concept. It assumes that we

- form aspirations of goal achievement (<u>aspiration formation</u>),
- then try to satisfy such aspirations by looking for means guaranteeing such goal achievement (<u>satisficing</u>), and
- finally adapt aspiration levels in the light of feedback information (<u>aspiration adaptation</u>).

Aspirations as discrete levels of goal achievement were considered in psychology early on and have been most prominently propagated by Simon (1955). An early attempt to model aspiration adaptation was made by Sauermann and Selten (1962). Nevertheless, like the theory of bounded rationality in general, the satisficing approach so far offers only an intuitive and natural terminology – already quite an achievement – but hardly any specific guidance when trying to predict (economic) decision behavior or to give advice like in teaching and consulting (see, e.g., Selten, 1998).

Since we consider the satisficing approach as the central concept of the theory of bounded rationality, this rules out its interpretation as perfect rationality in disguise or optimization under constraints (e.g., Rubinstein, 1998). Thus, aspiration levels can be both, aspects of preferences and restrictions of decision alternatives, illustrating that in bounded rationality theory the separation of means and ends, as known from the rational choice approach, may not apply.

Satisficing theory should also be clearly distinguished from actual behavior which may sometimes be rather inadequate. Inadequacy may result from not properly recognizing the essential structural aspects of one's decision environment, i.e., from inadequate mental representations as well as from yielding inadequately to emotions, e.g. by yielding to anger or frustration when having suffered a financial loss and trying to recover it immediately without proper risk analysis (see Tversky and Kahneman, 1991).

Our interpretation of bounded rationality also rules out mixing in psychological concepts which may have some empirical validity but do not rely on adequate perception of the decision environment.[1] More basically, bounded rationality may neither correspond closely to rationality theory nor be consistent with some psychological theories. Whereas rationality does not pay much attention to our limited cognitive capabilities, some of our behavior may neglect important structural aspects of the decision environment. One clearly has to distinguish not only between perfect and bounded rationality but also separate the two from behavior that is simply inadequate.[2]

We do not exclude that satisficing plus aspiration adjustment may converge to become optimal behavior, given adequate feedback information. But to postulate this without formally defining the two processes and applying them to specific (classes of) decision tasks is pure speculation (Beckenkamp, 2004). Whatever questions perfect rationality questions constraint optimization even more since such problems are often more demanding and not at all in line with our cognitive limitations. Constraint optimization is thus no bounded rationality approach, as interpreted here. Psychological effects, claiming inadequate reactions (like framing effects, see Pruitt, 1967, and Kahneman and Tversky, 1979) or emotions (e.g., getting upset after buying underpriced items and learning that they are cheap imitations), are neither perfectly nor boundedly rational as they do not rely on an adequate mental representation of the decision environment. Of course,

[1] Certain psychological theories like, e.g., reinforcement learning on which we likely rely when not knowing well enough our decision environment (see Bush and Moseller, 1955, Roth and Erev, 1998), may be entirely inadequate when becoming aware of one's decision environment.

[2] The latter category questions the view that our behavioral repertoire is "ecologically rational" (see, e.g., Gigerenzer and Todd, 1999). Naturally, we learn and thereby improve our behavioral repertoire (see Güth, 2000), but in our continuously changing habitat, we often may not be quick enough to adequately react to new important aspects.

how adequate a cognitive perception is depends crucially on what one knows about the decision environment. We speak of inadequacy only when the mental representation is at odds with what one can reasonably deduce from what one knows about the decision environment. What is “reasonable” depends, of course, on our limited cognitive abilities and how relevant the task is.

To render the satisficing approach more applicable, we consider rather specific decision tasks for which aspiration formation, satisficing behavior, and aspiration adjustment in the light of feedback information are rather natural, and for which aspirations clearly and formally delineate the set of satisficing behavior. Furthermore, to avoid purely theoretical speculation without empirical confirmation, we rely on experimental data. Partly our data question rather than confirm the satisficing hypothesis. This may in part be due to the experimental procedure, to our rigorous mathematical interpretation of aspirations, and/or to the stochastic nature of the decision tasks rendering aspiration formation, satisficing, and aspiration adjustment more difficult.

Let us explain in more detail how our satisficing approach differs from usual ways of analyzing satisficing behavior. One difference is that we focus on decision tasks with just one (numerically specified) objective, whereas others mostly consider multi-objective tasks (see, e.g., Selten, 1998). When applying satisficing theory more or less rigorously, decision makers usually are moreover confronted with unknown decision environments, e.g. in the sense that one only learns over time, i.e., during the search for satisficing options, which alternatives will be available (see Simon,1955, for a more general discussion). In the experiments reported below, participants are from the very beginning fully aware (after having correctly answered control questions) of their choice set. However, they will typically decide on only few alternatives for which they then check whether they are satisficing or not.

More importantly, an aspiration ladder or aspiration profile usually specifies a few numerically different achievement levels by which one judges how satisfactory an alternative is. Here we also consider such aspiration ladders but with quite a different interpretation: Rather than specifying a more ambitious goal achievement level, a higher aspiration is meant to apply to a better state of nature providing better chances to achieve a more ambitious result. Thus, different aspirations apply to different states of nature. When adjusting aspirations in the light of former experiences (in the experiments, we provide feedback information on former results), one can also adjust one or more components of one's aspiration profile. The satisficing hypothesis in the sense that what one has chosen is satisfactory for all possible states of nature is rather demanding. Although it is easily checked for a given alternative (one simply checks for all states of nature whether the result is satisfactory), it may be rather difficult to determine whether a satisficing alternative exists at all.

We first introduce the basic class of decision tasks (section 2) for which we then elaborate the satisficing approach with its three subprocesses, namely aspiration formation, satisficing, and aspiration adjustment more formally (section 3). We then report on the first experimental studies (section 4), mainly comparing boundedly with unboundedly rational behavior. Under "task transcending satisficing," we discuss (section 5) experimental data illustrating how satisficing behavior in one task may be related to such behavior in another, more or less related task. Without individually constant characteristics of satisficing, bounded rationality theory would be deemed to be case specific. In the light of the experimental data, we finally explore the absorbability of the satisficing approach, i.e., whether one continues to be satisficing when becoming aware of it (section 6), before concluding (section 7).

I. Portfolio selection tasks

In general, the class of stochastic decision environments can be defined by $R_{m,n}$-return rate matrices, whose elements r_{ij} are the return rate of asset $j = 0,1,...,m$ in state $i = 1,...,n$, plus possibly[3] a probability assignment for all n states of the world. Here we confine our description to the specific situations which we explored experimentally.

Let $e(> 0)$ denote the decision maker's credit line of interest-free borrowing which can be invested in

- idle money (amount $i_0 \geq 0$) with a return rate of 1
- a risk free bond (amount $i_1 \geq 0$) with a constant return rate of $r\left(> 1\right)$
- one or several risk assets (amount $i_j \geq 0$ for $j = 2,...,m(\geq 2)$)

where, of course, the budget constraint

$$\sum_{j=0}^{m} i_j = e$$

must hold. In our experimental scenarios, the risky assets $j = 2,...,m$ could only have binary return rates, which are low $(l_j < 1)$ in some states of the world and high $(h_j > r)$ in other states. We assume that the states of the world $s = 1,...,n(\geq 2)$ are well ordered in the sense that in state $s+1$ exactly one additional asset has a high rather than low return rate when compared to state s. In other words: the larger the state index the better the returns. The class of portfolio selection tasks can be easily generalized, e.g. by introducing interest for borrowing or by allowing for different probabilities of states. By assuming that all states are equally likely, we just try to avoid as far as possible the problem of probability transformation like, for instance, in cumulative prospect theory (Tversky and Kahneman, 1992).

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[3] Since the satisficing approach is non-Bayesian, it can be applied even when the probability assignment is missing.

Investment types	*Monetary returns in state*	
	1	2
i_0	i_0	i_0
i_1	ri_1	ri_1
i_2	$l_2 i_2$	$h_2 i_2$

Table 1: The simplest return rate matrix $R_{2,2}$ with $m = 2 = n$.

In Table 1, we have listed the possible returns of the possible portfolios (i_0, i_1, i_2), with $e = i_0 + i_1 + e_2$ for the simplest case $m = 2 = n$ with only one risky asset and two (equally probable) states 1 and 2. Since all experimental findings so far rely either on this simplest case or on the more complex one with $m = 3 = n$, we also illustrate this other case in Table 2. Whereas in the worst (best) state 1 (3) both risky assets yield low (high) returns, only asset i_2 realizes its high return rate (h_2) in the intermediate state 2.

Investment types	*Monetary returns in state*		
	1	2	3
i_0	i_0	i_0	i_0
i_1	ri_1	ri_1	ri_1
i_2	$l_2 i_2$	$h_2 i_2$	$h_2 i_2$
i_3	$l_3 i_3$	$l_3 i_3$	$h_3 i_3$

Table 2: The more complex return rate matrix $R_{3,3}$ case with $m = 3 = n$.

To render all risky assets reasonable choice alternatives in view of expected (monetary) value orientation, we require

$$L(j)l_j + H(j)h_j > L(j-1)l_{j-1} + H(j-1)h_{j-1} > nr > n$$

for $j = 3,...,m$. Here $L(j)$ or, respectively, $H(j)$ denotes the number of (equally probable) states $s = 1,...,n$ for which risky asset j yields its low l_j or, respectively, its high return rate h_j. For the case in Table 2, this simply requires

$$l_2 + h_2 > 2r > 2$$

and for the one in Table 3

$$2l_3 + h_3 > l_2 + 2h_2 > 3r > 3\,.$$

Thus, when only interested in the expected monetary return, one should invest everything in m-th risky asset, i.e., choose the portfolio with $i_m = e$. However, since we also impose

$$0 < l_j < l_{j-1} < 1 < r < h_{j-1} < h_j$$

for $j = 3,...,m$, one may shy away from expected value orientation due to the increasing risk with increasing asset index j. We rely on these assumptions for the scenarios in Tables 1 and 2 when elaborating the satisficing approach and discussing its validity in the light of experimental data.

II. The satisficing approach in portfolio selection

In trying to specify how aspirations are formed, the basic difficulty is to predict how many achievement levels one wants to distinguish for the various goals. Experimentally, one might leave it to each individual participant how rich the various aspiration ladders are or impose the same ladder structure for all participants. The surprisingly clear-cut confirmation of aspiration balancing (in negotiations both parties concede equally often in aspiration steps, see Tietz et al., 1978, Tietz, 1992 and 1997, Selten, 1998) is, for instance, based not only on imposing a given structure of the aspiration ladder but also on imposing the same structure for both parties. Obviously, this renders the concession steps by both parties interpersonally comparable which, in turn, allows and even suggests aspiration balancing.

The major advantage of concentrating on the class of portfolio selection tasks introduced above is that they not only suggest an unambiguous monetary goal, namely the monetary returns from investing, but also the forming of state-specific aspirations. Confronted with the multiplicity of (equally probable) states of the world, an investor may be induced – and in the experiments, this will actually be done – to determine a return aspiration for each state of the world and, naturally, higher ones for higher state indices since states are ordered monotonically from worst (state 1) to best (state n). Let us denote by A_s the return aspiration for state $s=1,...,n$ where bounded rationality obviously requires

$$A_s \geq A_{s-1} \text{ for } s=2,...,n.$$

For the simplest case $m=2=n$, illustrated in Table 1, the two return aspirations A_1 and A_2 with $A_2 \geq A_1$ imply for a satisficing portfolio $i=(i_0,i_1,i_1)$ the inequalities

$$i_1(r-1)+i_2(l_2-1) \geq A_1$$

and

$$i_1(r-1)+i_2(h_2-1) \geq A_2.$$

Since even an only boundedly rational investor will not leave money idle (since investing in the riskless bond is better), this can be simplified (for $i_o=0$) to

$$(e-i_2)(r-1)+i_2(l_2-1) \geq A_1 \text{ or } \frac{e(r-1)-A_1}{r-l_2} =: \bar{i}_2 \geq i_2$$

and

$$(e-i_2)(r-1)+i_2(h_2-1) \geq A_2 \text{ or } i_2 \geq \underline{i}_2 := \frac{A_2-e(r-1)}{h_2-r}.$$

This suggests the restriction

$$A_2 \geq e(r-1) \geq A_1$$

for boundedly rational aspiration formation. To render satisficing at all possible, one needs $\bar{i}_2 \geq \underline{i}_2$ or

$$e(r-1)(h_2-l_2) \geq A_1h_2 - A_2l_2 + r(A_2-A_1).$$

Only when these requirements are fulfilled is the set of satisficing portfolios $(i_0=0,i_1,i_2)$ non-empty. But even when this set is non-empty, an investor might choose something non-satisfactory when free to choose (as actually observed in our experiments).

In the more complex task illustrated in Table 2, the corresponding restrictions are

$$i_1(r-1)+i_2(l_2-1)+i_3(l_3-1)\geq A_1$$

$$i_1(r-1)+i_2(h_2-1)+i_3(l_3-1)\geq A_2$$

$$i_1(r-1)+i_2(h_2-1)+i_3(h_3-1)\geq A_3\,.$$

Assuming again $i_0=0$ and thus $i_1=e-i_2-i_3$ yields the following linear inequalities:

$$i_2(l_2-r)+i_3(l_3-r)\geq A_1-(r-1)e$$

$$i_2(h_2-r)+i_3(l_3-r)\geq A_2-(r-1)e$$

$$i_2(h_2-r)+i_3(h_3-r)\geq A_3-(r-1)e$$

Again, one can derive from these requirements when the set of satisficing portfolios $(i_0=0,i_1=e-i_2-i_3,i_2,i_3)$ in the two-dimensional i_2,i_3-simplex $\left\{(i_2,i_3)\in\mathbb{R}_+^2 : i_2+i_3\leq e\right\}$ is (non)-empty.

More generally, an aspiration ladder $A=(A_1,...,A_n)$ with $A_s\geq A_{s-1}$ for $s=2,...,n$ specifies an aspiration A_s for each state $s=1,...,n$ of the world. Assuming $i_o=0$ and thus $i_1=e-\sum_{j-2}^{m}i_j$ a portfolio $i=(i_o=0,i_1,i_2,...,i_m)$ with $i_j\geq 0$ for $j=1,...,m$ and $i_1+...+i_m=e$ is said to satisfy A if

$$\sum_{j\in L(s)}(l_j-r)i_j+\sum_{j\notin L(s)}(h_j-r)i_j+(r-1)e\geq A_s \text{ for all } s=1,...,n$$

with L(s) denoting the risky assets with low return rate in state s.

A decision maker is a potential satisficer if for his aspiration ladder A there exists a satisficing portfolio and an actual satisficer if he actually realizes a portfolio i satisficing his aspirations. Note that, even in case of $i_o>0$, a portfolio i can be satisficing. But when checking whether for an aspiration ladder A satisficing is at all possible, one can rely on the conditions above and on $i_o=0$. For any aspiration ladder the possibly empty set S of satisficing portfolios $i=(i_o=0, i_1, i_2, ..., i_m)$ with $i_o=0$ is thus the intersection of n linear half-spaces. To check whether an aspiration ladder A allows for satisficing, some of the inequalities in the conditions above can be used as equalities in the unknowns $i_2, ..., i_m \geq 0$ with $i_2+...+i_m \leq e$. If the remaining inequalities can then also be satisfied, the set S of satisficing portfolios is non-empty.

III. Experimental evidence

The first experiment (Fellner, Güth, and Maciejovsky, 2005) concentrated on the scenario of Table 1 with

$e=1000, l=.8, r=1.1, h=1.6.$

Participants played 17 successive rounds with return feedback in between, although only a randomly selected round was paid (to avoid diversification effects). The two treatments rely on the same protocol for the first round with

(i) reading the instructions and answering control questions,

(ii) stating aspirations A_1 and A_2 where only $A_1 < er$ has been imposed,

(iii) choosing the portfolio $i=(i_0, i_1, i_2)$, and

(iv) determining the probability $\hat{p}$ at which one would be indifferent between $i=(0,e,0)$ and $i=(0,0,e)$.

The latter answer $\hat{p}$ allows to compare the cheap-talk aspiration data (A_1, A_2) with cheap-talk risk aversion parameters $\alpha(\hat{p})$, inferred from $\hat{p}$ when assuming that the cardinal utility of money x is measured by x^α. Another incentivized elicitation of α is given by $\alpha(i)$, i.e., when considering i with $i_o=0$ as the optimal portfolio in view of the cardinal utility function x^α.

The later rounds differed according to treatment with the partial repetition treatment (PR) only repeating stage (iii), and the complete repetition treatment (CR) only excluding stage (i). For each treatment we employed 48 participants whose decision data qualified as independent observations yielding 48x17=816 portfolio choices per treatment.

Treatment	Satisficing	
	Potentially but not actively	Actively
CR	23.2 %	47.8 %
PR	27.8 %	36.8 %

Table 3: Actively and only potentially satisficing per treatment (% for 816 *i*-choices per treatment).

If $\underline{i} \leq \bar{i}$ holds for the aspirations (A_1, A_2), we say that satisficing is possible. If, then, the actually chosen portfolio does (not) satisfy both aspirations, we speak of (potentially but not) actively satisficing. According to Table 3, about two thirds of all portfolio choices $i = (i_0, i_1, i_2)$ have been at least potentially satisficing. But not even half of all portfolios are actively satisficing.

This illustrates that the concepts of bounded rationality are not readily available but need teaching or consulting and learning, confirming our claim that not all behavior qualifies as boundedly (and, of course, also as unboundedly) rational. That learning can help is shown by the higher degree of actively satisficing for treatment (CR), offering participants to learn how to form realistic aspirations.

Period	CR		PR	
	$p(n=48)$	p	$p(n=48)$	p
1	.26	.08	.06	.69
2	.12	.41	.13	.36
3	.28	.05*	-.06	.71
4	.41	.00**	.10	.50
5	.38	.00**	.23	.12
6	.35	.02*	.06	.68
7	.36	.01*	-.02	.91
8	.50	.00**	.04	.79
9	.44	.00**	.05	.74
10	.32	.03*	.12	.43
11	.45	.00**	.13	.36
12	.55	.00**	.02	.91
13	.42	.00**	-.05	.74
14	.45	.00**	-.02	.92
15	.34	.02*	.14	.36
16	.54	.00**	.08	.58
17	.53	.00**	.15	.32

Note: ** and * denote significance on the 1 % and 5 % level, respectively.

Table 4: Spearman rank correlation of $\alpha(i)$ and $\alpha\left(\hat{p}\right)$

	CR								PR			
	$\alpha(i)$				$\alpha(\hat{p})$				$\alpha(i)$			
Period	A_1	A_2	(A_2-A_1)	(A_1+A_2)	A_1	A_2	(A_2-A_1)	(A_1+A_2)	A_1	A_2	(A_2-A_1)	(A_1+A_2)
1	-.35*	-.14	.07	-.21	-.27	-.15	.03	-.23	-.10	.21	.15	.18
2	-.32*	.15	.34*	.06	-.12	.05	.02	.03	-.05	.24	.09	.20
3	-.43**	.09	.36*	-.11	-.25	.02	.07	-.05	-.24	-.02	-.03	-.02
4	-.41**	.12	.25	-.05	-.34*	.00	.12	-.10	-.24	.21	.22	.15
5	-.22	.36*	.39**	.24	-.28	.11	.16	.00	-.34*	.17	.20	.05
6	-.11	.15	.25	.16	-.29*	.00	.09	-.09	-.22	.10	.09	.11
7	-.39**	.10	.20	-.02	-.35*	.09	.15	-.07	-.20	-.01	-.01	-.01
8	-.23	.15	.23	.08	-.27	-.12	.04	-.16	-.17	.10	.10	.07
9	-.32*	.11	.31*	.02	-.24	.03	.10	-.03	-.27	.27	.27	.17
10	-.31*	.12	.23	.03	-.26	-.05	.13	-.13	-.33*	.11	.17	-.02
11	-.36*	.02	.27	-.03	-.26	.00	.11	-.06	-.33*	.26	.30*	.14
12	-.41**	.19	.35*	.04	-.40**	.05	.18	-.08	-.27	.12	.14	.05
13	-.31*	.32*	.39**	.23	-.23	.19	.23	.11	-.16	.04	.02	.05
14	-.32*	.31*	.37**	.22	-.30**	.13	.18	.09	-.26	.26	.26	.17
15	-.22	.30*	.36*	.21	-.27	.12	.21	.10	-.34*	.28	.33*	.13
16	-.33*	.27	.36*	.12*	-.34**	.17	.25	.08	-.31*	.11	.13	.02
17	-.37**	.34*	.44**	.22	-.29	.10	.18	.01	-.18	.17	.16	.18

Table 5: Spearman rank correlation of $\alpha(i)$ and $\alpha(\hat{p})$ with aspirations.

From the actually chosen portfolio $i=(i_0,i_1,i_2)$ as well as from the answer $\hat{p}$ on stage (iv) of the decision process in each (CR)-round and in the first round of (PR), we can infer risk attitude estimates $\alpha(i)$ and $\alpha(\hat{p})$ when assuming the cardinal utility specification x^α and optimality. Assuming $i_0=0$, all $i_2 \leq 66.67$ are identified with $\alpha(i)=0$ and all $i_2 \geq 333.33$ with $\alpha(i)=1$. In treatment (CR) after round 2, the so deduced (normative) risk preference parameters $\alpha(i)$ and $\alpha(\hat{p})$ are significantly and positively correlated (Table 5).

Furthermore, $\alpha(i)$ and partly also $\alpha(\hat{p})$ are positively and significantly correlated with aspiration data, mainly A_1 and the aspiration spread A_2-A_1. This suggests that aspiration data offer new ways of defining risk attitude (e.g., via the spread A_2-A_1 or the sum A_1+A_2 of aspirations) which, in our view, are far more convincing than the utility of the money approach. The aspiration spread $A_2-A_1(>0)$, describing how much more one aspires in the best than in the worst state, seems a very intuitive and plausible indicator of risk taking. Similarly, the sum A_1+A_2 could express optimism in the sense of high demands regardless of the state.

In their experimental study, Fellner, Güth, and Martin (2006b) have first confronted participants with both routines, namely

(S) the satisficing approach (participants choose (A_1,A_2) and learn whether they are consistent, i.e., define a non-empty set of satisfactory portfolios; may, in case of consistency - and must, if not - revise their aspirations)

(O) the optimality approach (participants choose $\alpha \geq 0$ and learn about the $u(x) = x^{\alpha}$ optimal portfolio; may change α and thus indirectly their portfolio).

Half of the participants first experience (S) and then (O) repeatedly; for the other half, the order of (S) and (O) is reversed. In the final phase, participants were free to choose either routine repeatedly. Actually, (S) was chosen in 38 % of all cases, leaving a residual share of 62 % for (O). Only 31 (16) of altogether 63 participants constantly selected (O) or, respectively, (S). Most adjustments, when using either routine (S or O), were minor (see Figures 1 and 2), regardless whether aspirations were adapted or α revised.

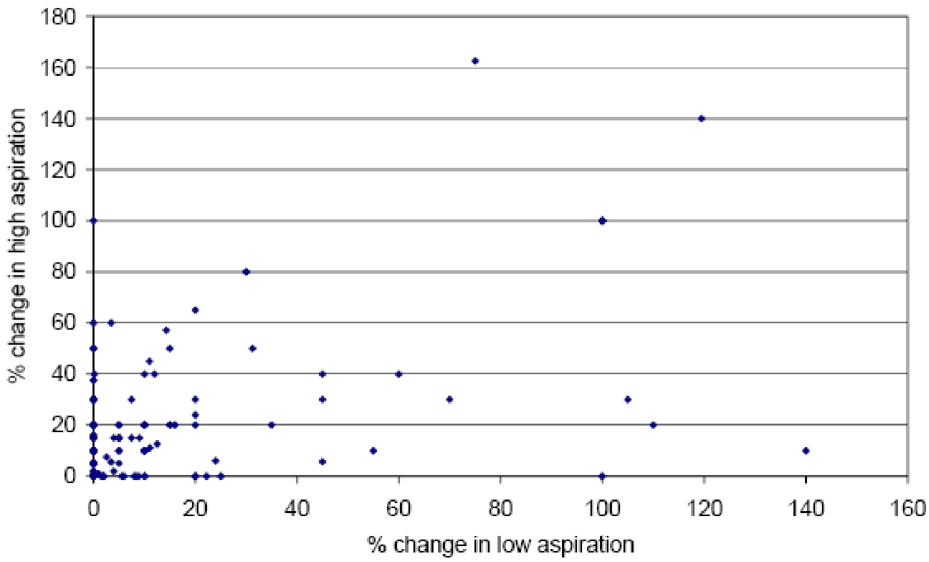

Figure 1: Adjustments of aspirations.

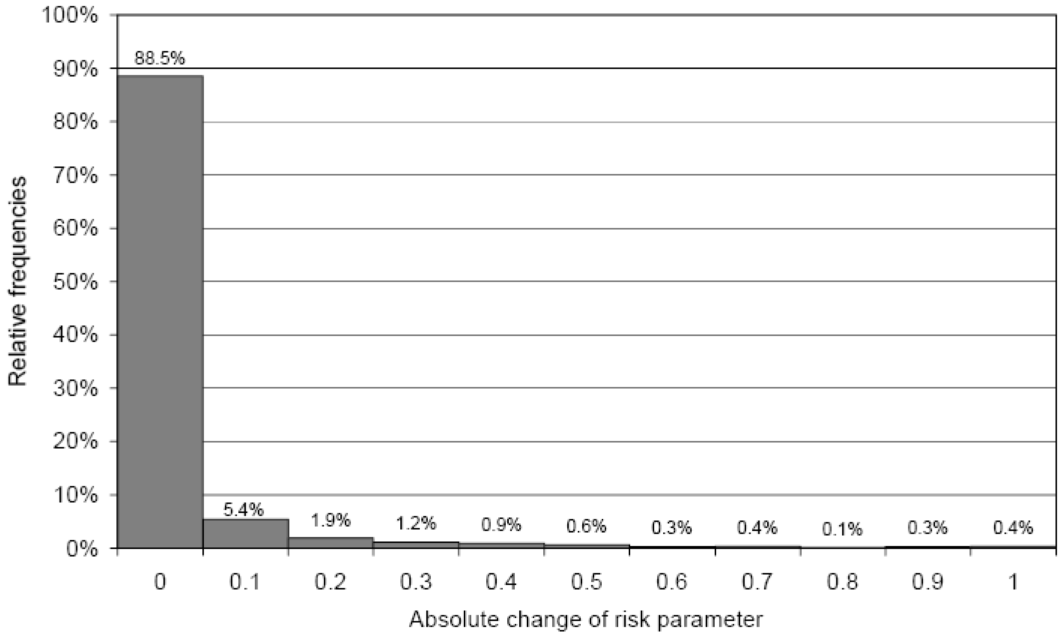

Figure 2: Absolute change of the risk parameter α.

IV. Task-transcending satisficing

According to the cardinal utility concept, an individual's attitudes toward risk is determined by the curvature of the utility of money-curve. If this curve is concave/linear/convex, the decision maker is risk averse/neutral/loving. It is rather obvious and has often been illustrated experimentally that the often complex considerations of how to cope with risk are at best only poorly captured by whether the marginal utility of money is decreasing/constant/increasing (for an older survey, see Camerer, 1995). There is, however, a tremendous advantage that goes with the cardinal utility approach: After specifying the risk preferences of the decision maker one can apply it, except for possible computational difficulties, to all (sorts of) decision tasks, i.e., one can apply such an evaluation concept universally to predict decision behavior. Although these predictions usually fail, it seems to be quite an advantage that one can at least derive such predictions. For the satisficing concept such universal applicability is by no means granted and rather questionable.

Rather than conceding from the outset that the satisficing approach has to be case specific,[4] let us explore whether there are constant individual characteristics in satisficing behavior when facing different (sorts of) decision tasks. Are there aspects of satisficing behavior which carry over from one decision task to another and, if so, which are the likely features of such task-transcending satisficing?

If the number of states is too large for a fully elaborated aspiration ladder, one will more or less often specify aspirations $A_s = A_{s-1}$. The richness of the aspiration ladder, measured by the number of different aspirations for a given aspiration ladder $\mathrm{A} = \left(A_1, ..., A_n\right)$, may be a personal characteristic in the sense that somebody with a richer ladder in one task will rely on a richer ladder in other tasks as well. Since we have no experimental evidence for large numbers n of states (so far, we have only data for $n = 2$ and $n = 3)$, we will not discuss this in more detail to avoid speculating without facts.

For smaller numbers n, as in Tables 1 and 2, a straightforward candidate is the spread $A_n - A_1$ or the sum $A_1 + A_2$ or, respectively, $A_1 + \left(A_2 +\right) A_3$ of the aspiration ladder. In their experiment, Fellner, Güth, and Martin (2006a) confronted participants with various parameter constellations, both for Table 1 and Table 2. In their experiment A, the overall correlation of the individual's average spread $A_2 - A_1$ (Table 1 – tasks with $n = 2$) and the same individuals' average spread $A_3 - A_1$ (Table 2 – tasks with $n = 3$) is, with .44, highly significant $\left(p < .01\right)$ and only slightly smaller than the highly significant correlation of $A_2 - A_1$ across Table 1 – tasks (experiment B). For the sum $A_1 + A_2$ or, respectively, $A_1 + A_3$ of the lowest and highest aspiration, the correlation is even stronger (see Tables 6 and 7). Similar confirmative evidence can be obtained by median splits: Participants in the lower or, respectively, upper half of the observations for different $R_{2,2}$ – and/or

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[4] Such case specificity has also been claimed to apply for the cardinal utility approach (e.g. Karni and Schmeidler, 1990).

$R_{3,3}$ – tasks usually end up in the lower or, respectively, upper half for other such tasks (see Fellner, Güth, and Martin, 2006a, for details).

$R_{3,3}$				
$R_{2,2}$	A_1	A_3	$A_3 - A_1$	$A_1 + A_3$
A_1	0.82**	0.73**	0.28	0.76**
A_2	0.60**	0.73**	0.46**	0.72**
$A_2 - A_1$	0.02	0.29*	0.44**	0.26*
$A_1 + A_2$	0.67**	0.81**	0.48**	0.80**

Note: ** and * denote significance on the 1% and 5% level, respectively.

<u>Table 6:</u> Spearman rank correlation of aspiration measures across tasks in experiment A (participants decide for $R_{2,2}$ - and $R_{3,3}$ -tasks).

$R''_{2,2}$				
$R'_{2,2}$	A_1	A_3	$A_2 - A_1$	$A_1 + A_2$
A_1	0.65**	0.44**	-0.04	0.52**
A_2	0.43**	0.71**	0.43**	0.71**
$A_2 - A_1$	-0.03	0.39*	0.56**	0.34*
$A_1 + A_2$	0.50**	0.68**	0.36**	0.70**

Note: ** denote significance on the 1% level.

<u>Table 7:</u> Spearman rank correlation of aspiration measures across tasks in experiment B (participants decide for $R_{2,2}$ -tasks only).

V. Is satisficing absorbable?

Assume that a theory, e.g., our specification of satisficing behavior for the special class of decision tasks, correctly describes how decisions are made and that the decision maker(s) become(s) aware of the theory. If then the decision maker(s) still behave(s) in line with the theory, we say that the theory is absorbable (cf. Güth and Kliemt, 2004, for a more general discussion). Becoming aware of a theory, e.g., the one of Satisficing in Portfolio Selection developed above, can result from hiring a consultant, teaching, and learning. Given the insights from the theory and the cognitive capabilities, which the theory requires, agents with such skills should not see an advantage in deviating from the theory. In the case of one-person decision making,[5] as studied here, this simply means that a satisficer may update his aspirations but sees no advantage in giving up satisficing at all.

To investigate the absorbability of the satisficing approach experimentally, one could rely on “think aloud” studies or on experiments where the investor role is taken by a team of participants whose discussions are (video)taped. Here one might distinguish those who are clearly aware of their satisficing behavior and others who are not. Another possibility would be to induce absorption by teaching, e.g. by a lecture on the Satisficing Concept before the experiment. Güth, Levati, and Ploner (2006) have tried to experimentally induce absorption of satisficing not by “indoctrination” but only by “familiarity.” More specifically,

- participants are first familiarized with the satisficing routine[6] (one first specifies an aspiration ladder, revising it until all aspirations can be met, but is ultimately free to choose a (non)satisficing portfolio, knowing whether or not it is satisficing) and induced to use it,
- before, in the second phase of the experiment, they can freely decide whether to stick to the satisficing approach or freely choose their portfolio, but have to specify their aspirations in either case.

Participants were informed how in the scenarios? of Tables 1 and 2 the aspirations (A_1, A_2) or, respectively, (A_1, A_2, A_3) plus the (un)bounded rationality requirement $i_0 = 0$ restrict i_2 or, respectively, jointly i_2 and i_3, and that the satisficing set may be empty if the aspirations are too ambitious. In the latter case,

[5] When interacting strategically, an absorbed theory will imply true expectations. Thus, the main difference of an absorbed behavioral theory of game playing to normative game theory, whose equilibrium concept requires only optimality in addition to true expectations, is that it has to substitute optimality.

participants had to adapt their aspirations before (being able to) they could actually determine their portfolio $i=(i_0,i_1,i_2)$ or, respectively, $i=(i_0,i_1,i_2,i_3)$.

The cases of two states $(n=2)$ and of (the) three states $(n=3)$ were explored in a between-subjects design with changing parameters l,r,h or, respectively, L,l,r,h,H in every round. In the first six rounds (phase 1), participants invariantly had to use the "decision aid," i.e., the satisficing routine. In the next six rounds (phase 2), they were free to continue using it or to select their portfolio unaided, but were always asked for their aspirations.

Table 8 lists various averages, means, and standard deviations of crucial variables like profit, aspirations $A_1, A_2\,(\text{and}\,A_3)$, the investment i_1 in the riskless bond, i_2 $(\text{and}\,i_3)$, separately for both treatments (two vs. three states) and for phases 1 and 2. N is the number of observations. Whereas for two states, profits and aspirations increase considerably from phase 1 to phase 2, in the three-state scenario, this is restricted to the profit and the aspirations A_1 and A_2, with A_3 decreasing. One overall tendency is that the spreads A_2-A_1 or, respectively, A_3-A_1 decrease from phase 1 to phase 2.

Figure 3 reveals a very low tendency to rely on the "decision aid" when participants are free to use it. Rather surprisingly, the use of the "decision aid" is stronger in the simpler two-state scenario for which it is also rather stable. One reason for the scarce use could be, of course, that after experiencing it six times in phase 1, participants have already internalized the satisficing routine sufficiently to achieve satisfactory choices without relying on the "decision aid." As shown in Figure 4, about 40 % of all unaided choices in the two-state scenario are indeed satisficing, whereas this is true only half as often in the three-state scenario.

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[6] The instructions refer to this as using a „decision aid."

Even when being required to use (phase 1) or voluntarily using (phase 2) the “decision aid,” participants could nevertheless choose a non-satisfactory portfolio. The dynamics of aided satisficing are visualized in Figure 5. Compared to phase 1, there is a considerable improvement in phase 2: Those who voluntarily rely on the “decision aid” are apparently more likely to choose a satisficing portfolio. Quite surprisingly, the change from two to three states seems to indicate already a considerable increase in cognitive demands, both when using the satisficing routine (29.17 % of the participants rely on equal aspirations for different states in the three-state scenario and only 16.13 % in case of two states) and when deciding unaidedly.

Treatment	Phase	N	Variable	Mean	Median	Standard deviation
Two-state	1	186	Profit	51.38	20.00	153.47
			A_1	-43.61	0.00	104.51
			A_2	109.87	30.00	157.44
			i_1	632.80	800.00	392.15
			i_2	333.33	200.00	387.52
	2	186	Profit	100.42	56.25	176.12
			A_1	68.64	0.00	264.97
			A_2	178.01	100.00	209.12
			i_1	613.36	800.00	369.35
			i_2	366.48	200.00	370.93
Three-state	1	192	Profit	111.71	37.00	351.72
			A_1	-72.73	0.00	160.59
			A_2	14.75	20.00	176.63
			A_3	187.36	40.00	381.78
			i_1	472.98	500.00	371.07
			i_2	302.73	200.00	309.56
			i_3	161.27	50.00	265.26
	2	192	Profit	180.75	100.00	427.66
			A_1	128.15	10.00	277.21
			A_2	145.64	100.00	214.18
			A_3	156.14	95.00	258.94
			i_1	478.26	550.00	352.77
			i_2	307.16	200.00	295.55
			i_3	156.77	50.00	268.00

Table 8: Descriptive statistics on aspiration levels and investment decisions separately for phase 1 (periods 1-6) and phase 2 (periods 7-12) and the two $\left(R_{2,2}\right)$ or, respectively, the three $\left(R_{3,3}\right)$-treatment.

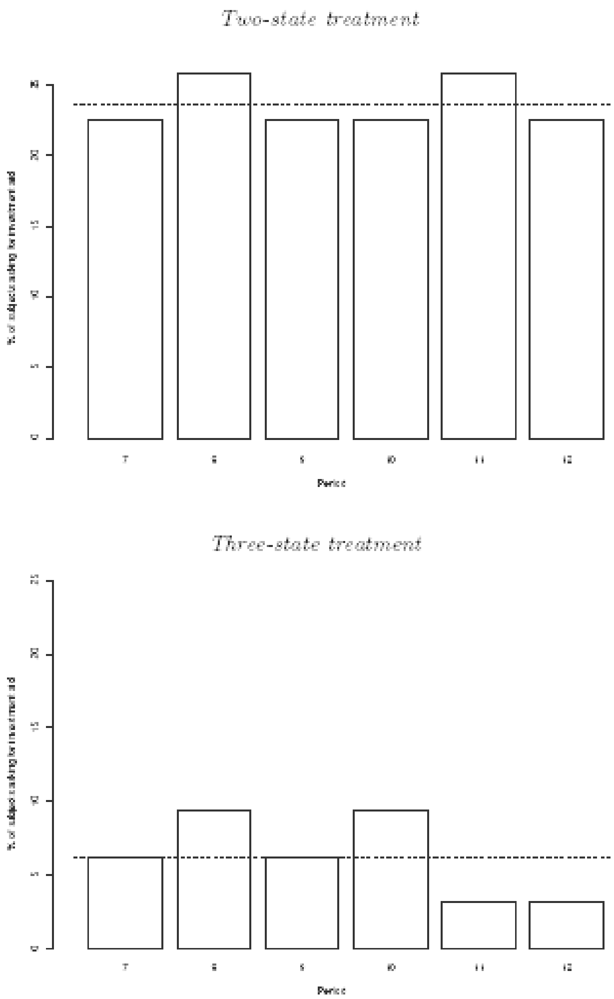

Figure 3: Percentage of subjects asking for the decision aid in each period of phase 2.

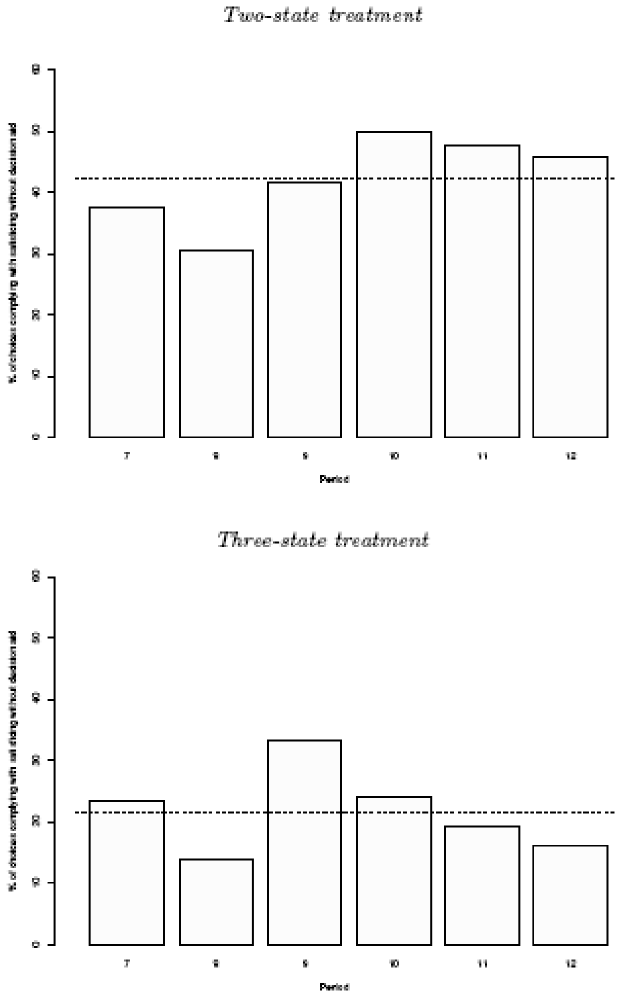

Figure 4: Frequency of choices not supported by the decision aid, which agree with satisficing behavior in each period of phase 2.

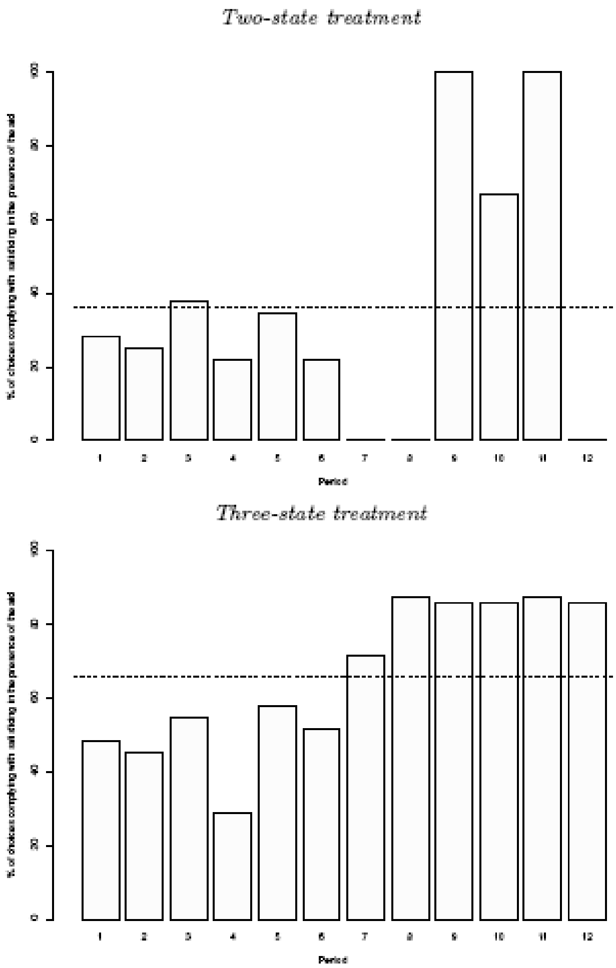

Figure 5: Frequency of choices not supported by the decision aid, which are consistent with aspirations in each period of the experiment.

VI. Conclusions

For the specific investment problems with $m+1$ investment options, including idle money and a riskless bond, and n states of nature, it has been assumed and experimentally guaranteed that investors specify state-specific aspirations. Further, simplifying assumptions are that states are well ordered from worst to best and that all risky assets have only binary return rates.

For any aspiration vector (or respectively, aspiration ladder specifying a higher return aspiration for a better state) the set of satisficing portfolios is rigorously defined as the intersection of linear half-spaces which may, however, be empty. It has been explored with the help of data from different experiments

- whether participants specify consistent aspirations in the sense that the set of satisficing portfolios is non-empty and, if so, actually choose a satisfactory portfolio,
- how such cheap-talk aspirations and especially their spreads are related to risk attitude, as defined by the curvature of "utility of money" and inferred from either the investment choice or a cheap-talk answer,
- whether participants prefer satisficing over optimizing when having experienced both routines and are then free to rely on either one,
- whether there are individual constants in satisficing across tasks of the same or different complexity, and
- whether participants go on with satisficing after absorbing it.

So far, the results are partly encouraging and partly not. With more experience participants more often specify consistent aspirations which also capture, especially by their spread $A_n - A_1$, minimum A_1 and their sum $A_1 + ... + A_n$, risk attitudes in a very intuitive way and which, on the individual level, are rather stable across tasks.

On the other hand, many participants have great difficulties to generate consistent aspirations, especially when the tasks become more complex. Given such difficulties of some participants, it is surprising that they reject the help of the Satisficing Routine which would help them to check the consistency of aspirations and should speed up the process of aspiration adaptation.

This mixed evidence may simply indicate that bounded rational decisions are not always easily derived. What may actually be required are serious cognitive efforts to mentally model the essential aspects of the decision environment, to generate satisfactory decision alternatives, and to compare them. In the decision tasks considered here, the investor can, of course, simplify matters, e.g. by stating very moderate aspirations which render satisfactory nearly all reasonable portfolios. In case of highly complex tasks (large m and/or n), one can expect satisficing in the strictest sense of consistent aspirations and realizing a satisfactory portfolio only when the investor does not specify fully differentiated aspiration profiles in the sense of $A_s \neq A_{s-1}$ for $s = 2, ..., n$.

Boundedly rational behavior may be difficult to derive and requires learning, consulting, teaching, which should, however, presuppose only cognitive capabilities and deliberation efforts which one can reasonably expect for the situation under consideration. Bounded rationality is thus clearly distinguished not only from the rational choice approach but also from heuristics which may be easily applicable but can be rather inadequate. Practical and helpful advice is better based on bounded rationality since, on the one hand, we do not fulfill the cognitive requirements of the rational choice approach and, on the other, should not follow heuristics whose adequacy could moreover be checked only by an at least boundedly rational analysis of the decision problem.

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