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A satisficing approach to eliciting risk preferences

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ABSTRACT

A new approach is proposed to eliciting risk preferences by framing choice over risky payoff distributions as a satisficing task. We demonstrate novel links between the information elicited from the satisficing task—which allows subjects to consider accepting a *worse* worst-case outcome in favor of a *better* best-case outcome—and portfolio choice using expected utility theory (EUT). The key tradeoff in our satisficing task can also be stated in reverse: to consider accepting less attractive potential upside gains in order to improve worst-case outcomes. Risk preferences are elicited by asking subjects to choose an acceptable worst-case portfolio outcome from a continuum of binary gambles, each with its own support and unique minimum. The *worst-case aspiration* represents the smallest low-state payoff in the binary gamble that the subject is willing to accept. We show analytically and empirically that choosing a most preferred worst-case aspiration maps into a logically equivalent—but psychologically distinct—process of expected utility maximization (i.e., allocating one's savings over a binary risky asset and risk-free bond using the EUT framework with a unique risk-acceptance parameter under CARA or CRRA risk preferences).

1. Introduction

This paper proposes a new approach to measuring risk preferences. Our approach elicits risk preferences using a satisficing task that asks subjects to consider how potential upside gains must be traded off to improve the (portfolio's) worst-case outcome. The satisficing task is an algebraic re-description of the simplest two-asset portfolio choice task of allocating investable funds between a risk-free asset and a binary risky asset with high and low states. We focus on how much gain must be sacrificed in the upside realization to achieve the subject's desired worst-case outcome (which we refer to as the *worst-case aspiration*). This re-description of the portfolio choice problem evokes new reasoning about tradeoffs in portfolio choice—in terms of the best best-case outcome given the subject's worst-case aspiration, as opposed to orthodox maximization of expected utility based on mean-variance preferences.

Our approach is grounded in Simon's (1959) notion of satisficing where decision makers use threshold-based rules. We apply satisficing of worst-case aspirations (i.e., choosing a "good enough" worst-case portfolio outcome) in the context of choosing a portfolio from a small menu of random payoff distributions. We propose a simple technique for measuring risk preferences and making interpersonal comparisons of risk attitudes using intuitive units of measure that are algebraically equivalent to expected return and standard deviation combinations.

The expected utility framework (Von Neumann & Morgenstern, 1944) is often used to estimate risk preferences.[1] Deviations from expected utility theory may arise as the result of limits on the decision maker's capacity to compute, to know, and/or to remember outcomes and probabilities (Simon, 1955, 1982).[2] Tversky and Kahneman (1974) refer to such violations of axiomatic consistency as behavioral biases, which have inspired models of bounded rationality conceived of as

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[1] In the EU framework, the preferences are assumed to be well-defined and satisfy the Savage axioms guaranteeing that risk preferences are representable as if they are solutions to an expected utility maximization objective.

[2] Abundant empirical evidence in economics, psychology and neighboring disciplines of decision science demonstrates that real-world choice data commonly violate EU theory, implying that those data cannot be rationalized as if it arose from a mental process of expected utility maximization (Allais, 1953; Camerer, 1992; Conlisk, 1989; Ellsberg, 1961; Rabin, 2000; Starmer, 2000).

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optimization subject to cognitive constraints (e.g., Conlisk, 1996; Day & Pingle, 1991; Simon, 1955, 1978).[3] Selten (1998) focuses on the setting of aspirations, fixed or adjusted, in satisficing processes. Selten hypothesizes that aspiration setting can provide a more descriptive and empirically relevant characterization of actual decision makers' search and stopping rules.

Our approach to measuring risk preferences takes as its point of departure the observation that people make economic decisions over risky payoff distributions without any need for translating outcomes and probabilities into the language of expected utility and symmetric measures of risk. Instead, people frequently set aspirations and then choose an alternative from their choice sets that meets aspiration levels (i.e., satisficing). People apply various techniques of simplification as adaptive responses to the demands of complex decision tasks, such as retirement savings and portfolio choice.[4] Small-scale farms, for example, often target a minimum acceptable level of revenue, which is achieved by cultivating "safe" crops that generate relatively stable returns from one portion of their land, while allocating the remainder of their land to "risky" crops with superior upside (Lopes, 1987). Herb Kelleher, founder and former CEO of Southwest Airlines, talks frequently about his focus on hedging fuel costs, which can be interpreted as locking in a worst-case aspiration for earnings, similar to the decision variable used in our elicitation technique. Adopting simplicity as a guiding principle, Kelleher attributes his company's success, in part, to its focus on targeting a maximum acceptable fuel cost while eschewing complex, multi-year planning, which he believes caused other airlines to struggle: "We have been successful because we've had a simple strategy. The lowest costs in the industry—that can't hurt you. . ." (Lucier, 2004).

We use satisficing decision rules as a means of eliciting subjects' rankings of lotteries because they are intuitive. Asking subjects to consider tradeoffs between best-case and worst-case payoffs is easier for subjects without probability and statistics training than asking them to express tradeoffs between standard deviation and expected value of lotteries. We show that information about subjects' choices over risky lotteries elicited using our satisficing elicitation tool can be transformed into conventional measures of risk aversion based on expected utility theory.

Our elicitation technique asks subjects to invest in a two-asset portfolio consisting of a risk-free bond (with guaranteed return) and a binary risky asset with high and low rates of annual return that, for simplicity, are assumed to occur with equal probability. This structure is similar to the ones used in utility assessment methods (see Farquhar, 1984 for a review) such as certainty equivalence and probability equivalence but the satisficing approach is easier for subjects being natural and intuitive (Brown & Sim, 2009). The resulting satisficing decisions, which trade off larger potential losses (in the portfolio's worst-case outcome) for greater possible gains (or upside potential), are analytically related to the orthodox EU approach to risk-aversion. To our knowledge, our demonstration of this simple analytic relationship between elicited satisficing preferences and EU risk aversion is novel. Our two-asset portfolio decision with *satisficing* follows the design presented in Güth (2007) and further used in studies of satisficing and portfolio choice (Fellner, Güth, & Maciejovsky, 2009). A related satisficing decision procedure is Brandstätter, Gigerenzer, and Hertwig's (2006) *priority heuristic*. They argue that worst-case outcomes are typically more important than the probability of that worst-case outcome occurring. Minimum outcomes play a similarly important role in regret theory (Loomes & Sugden, 1982), disappointment theory (Bell, 1985), and failure avoidance (Heckhausen, 1991).

The satisficing elicitation technique gives focal importance to the choice of a worst-case payoff in levels (in our case, in Indian rupees, INR). At the outset, we elicit an initial amount (in INR) to be invested in a portfolio of assets. The portfolio allocation across risky equities and zero-risk bonds is to be decided next. The subject must then decide how to allocate the initial investment between a risk-free bond returning 10% and a binary risky gamble with equiprobable returns of + 32% and − 10% returns. The subject is free to change the initial investment after viewing the reward structure before finalizing the decision. All elicited amounts are in currency level (of INR) rather than as percentages (i.e., we do not elicit the portfolio by asking for any non-negative percentage-point increments summing to unity, as in the presentation of canonical portfolio choice problems in finance textbooks). Therefore, the portfolio choice decision is made in units of INR, with pre-testing and redundant cross-checking that alternate between percentage and level expressions used to describe investment returns. Finally, we elicit a *worst-case aspiration*, defined as the minimum acceptable portfolio outcome.

In the satisficing framing, tradeoffs presented to subjects between best-case and worst-case payoffs are constrained such that the subject's worst-case aspiration is respected.[5] We show that the tradeoff between more favorable worst-case aspirations and best-case portfolio gains represents an alternative elicitation scheme that is algebraically equivalent to risk aversion under the assumption of EU maximization. Viewing the portfolio chosen by satisficing from an expected utility perspective, one easily sees that choosing greater (i.e., more favorable) worst-case aspirations can be interpreted as a revealed preference for portfolios with the benefit of lower standard deviation traded off against lower expected value. The elicited worst-case aspiration and implied upper bound on the high-state portfolio return, jointly, produce an "optimal" portfolio (i.e., greatest best-case aspiration given the subject's choice of worst-case aspiration).[6]

The paper is organized as follows. Section 2 details the simple and stylized portfolio choice task used for the purpose of elicitation and measurement of interpersonal variation in risk preferences. Section 3 describes the experimental design and descriptive statistics. Section 4 reports detailed descriptive information about subjects' risk preferences based on the aspiration data that demonstrates links between satisficing and the EU maximization approach; Section 5 provides further discussion and contextualization of our aspiration setting task within the bounded rationality literature. Section 6 concludes.

2. Aspirations and risk

Consider an individual who faces the task of allocating an amount e between the risk-free bond earning constant gross return r (e.g., $r = 1.10$) and the risky investment X with low-state and high-state gross returns denoted l and h, respectively, and corresponding probabilities p and $1 - p$ (e.g., $l = 0.90$ with probability 0.50 and $h = 1.32$ with probability 0.50). If the entire amount e (i.e., the desired investment value (chosen by subjects in INR) is invested in the bond r, then the portfolio's terminal value is simply the product er. Similarly, if the entire amount is invested in the risky asset, then portfolio's terminal

[3] A subset of this bounded rationality literature relies on satisficing as a good-enough adaptive strategy across different kinds of environments with profound uncertainty (Simon, 1972).

[4] Environments with unknown action spaces and uncertain mappings from actions into payoff distributions provide further motivation for satisficing as a potentially adaptive response (Gigerenzer, Todd, & The ABC Research Group, 1999; Payne, Bettman, & Johnson, 1993).

[5] The possibility of unwanted demand effects on subjects when asked to evaluate lotteries using our satisficing elicitation tool leads to within-subject testing (reported below in Section 3) of risky choice with and without using the satisficing elicitation tool. Subjects make allocation decisions based on both approaches, and a substantial proportion prefers the allocation made using the satisficing elicitation technique.

[6] Subsequent analysis demonstrates links between satisficing and risk aversion in the orthodox expected utility approach. The notion of optimal best-case aspirations given subject's choice of worst-case aspiration is therefore equivalent to the well-known characterizations of optimality: greatest expected return given the subject's choice of standard deviation or, equivalently, the smallest standard deviation given subject's choice of expected return.

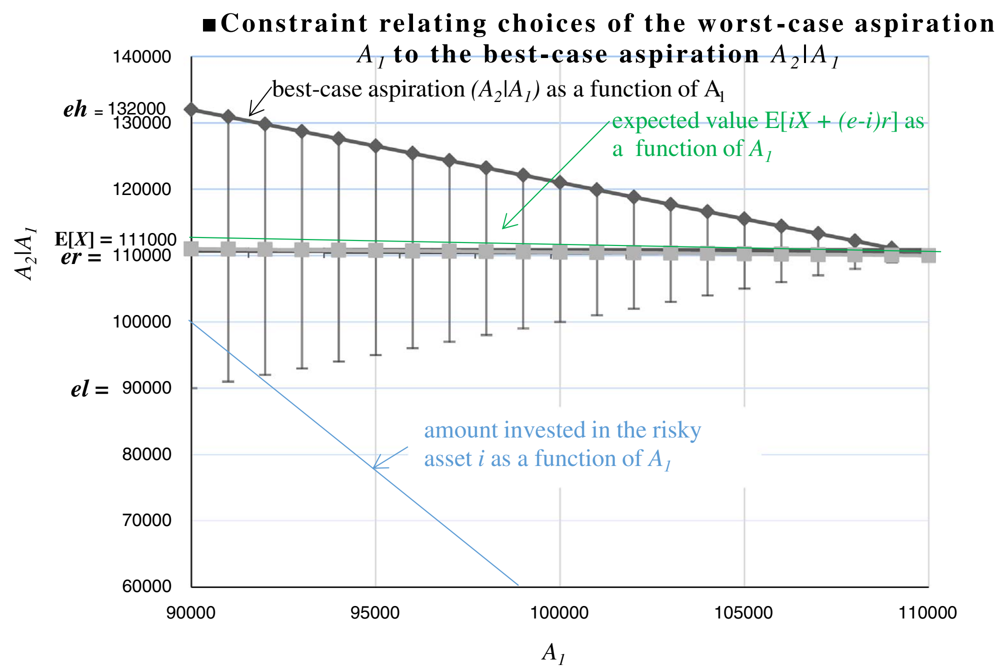

Fig. 1. Illustrates the aspiration pair $(A_1, A_2|A_1)$, which shows the tradeoff between worst-case and best-case aspirations. The more standard description of making a tradeoff between the portfolio's expected value and standard deviation (represented by the lengths of the vertical error bars in Fig. 1) is less intuitive (i.e., more difficult) for non-experts to visualize.

value *ex ante* is represented by the random value eX whose realized value is el with probability p or eh with probability $1 - p$. We assume that the low-state return is worse than the risk-free bond's return which is, in turn, less than the risky asset's high-state return: $l \le r \le h$.

Assuming no short-selling for simplicity (e.g., borrowing bonds to leverage > 100% of e into risk), terminal wealth is weakly bounded between the minimum and maximum possible terminal wealth values, el and eh, corresponding to 100% weighting on the risky asset in low and high realized states of the stochastic reward environment. Prior to committing to any particular allocation into bonds or the risky asset, our elicitation scheme asks subjects to specify desired investment amount e and a worst-case aspiration level A_1 that is weakly bounded below by the worst-case terminal wealth, el, and bounded above by the "safest" portfolio's realized value (when all wealth is allocated to the risk-free bond), er. That is: subjects are asked: "Choose the minimum acceptable worst-case value for your portfolio A_1 within the bounds $el \le A_1 \le er$." The portfolio weights that the subject chooses determine worst-case and best-case portfolio returns that satisfy $el \le A_1 \le A_2 \le eh$, following from the risky asset's two-outcome event space.

The aspiration A_1 can be achieved exactly *ex post* (in the event that the risky asset is realized in the low state) by an amount i to be invested in the risky asset such that when the worst-case low-state outcome is realized, the portfolio's terminal value is precisely the worst-case aspiration:

$$A_1 = r(e - i) + li, \quad \text{or equivalently,} \quad i = \frac{(er - A_1)}{(r-l)}. \tag{1}$$

Because the gross returns r and l are given exogenously by the reward structure in the decision environment (or experimental design) and because the subject has previously committed to the initial amount invested e, there is an obvious one-to-one equivalence between choosing A_1 and i (with only a single degree of freedom) in what are effectively re-parameterizations of a single choice variable. According to Eq. (1), the subject's choice of A_1 determines the value of i or, equivalently, choice of i determines the value of A_1.

Choosing $A_1 = r(e - i) + li$ also determines the portfolio's maximum possible value, which we refer to as the implicit best-*case aspiration* A_2:

$$A_2 = r(e - i) + hi. \tag{2}$$

Substituting $i = \frac{(er - A_1)}{(r-l)}$ from Eqs. (1) into (2) provides another simple linear formula expressing the best-case aspiration as a function of the worst-case aspiration:

$$A_2\Big|A_1 = \left(\frac{(er - A_1)}{(r-l)}h\right) + \left(e - \frac{(er - A_1)}{(r-l)}\right)r = -\frac{(h-r)}{(r-l)}A_1 + \frac{(h-l)}{(r-l)}er. \tag{3}$$

The subject has already committed to a choice of e when asked to choose A_1. The environment's stochastic reward structure as given by the experimental design provides values of r, l and h, which are not affected by the subject's choice variables. None of the expressions depend on p (although we provide the value $p = 0.5$ to avoid ambiguity and aid simplicity in our design).

Our elicitation technique encourages subjects to think about the tradeoffs that can be represented as easy-to-compute linear functions mapping the worst-case aspiration into simultaneous choices of i and A_2 (or equivalently, the portfolio's mean and standard deviation). Based on a subject's worst-case aspiration A_1, the resulting portfolio is a risky payoff with equiprobable terminal wealth values given by the pair $(A_1, A_2|A_1)$.

Subjects are encouraged to investigate the relationship between A_1 on the one hand and i and $A_2|A_1$ on the other: "Choosing a value of A_1 determines the amounts to be invested in the risky asset and the risk-free bond. Your choice of A_1 also determines the best possible portfolio value that can be achieved when the risky asset achieves the high outcome. Go ahead and experiment with different values and hit return when you are satisfied with your choice of A_1." The importance of *experiencing* a payoff distribution before choosing an action rather than basing choice solely on a description of its probability distribution is, by now, a well-established finding (Barron & Erev, 2003; Erev & Barron, 2005; Kaufman, Weber, & Haisley, 2013). For instance, Hogarth and Soyer (2015) argue for and provide empirical evidence suggesting that it is important to allow subjects to experience distributions rather than only communicating parameter values to describe those distributions, thus providing further motivation for our elicitation technique.

Fig. 1 shows contrasting re-parameterizations of the decision task contrasting our satisficing approach which emphasizes the tradeoff describing how A_1 maps into $A_2|A_1$ versus the orthodox EU tradeoff between expected return and standard deviation. The tradeoff between worst-case and best-case aspirations is likely to be more salient because: (i) the currency units measuring levels of payoffs in the worst-case and best-case aspirations avoid the unfamiliar statistical concepts of mean and standard deviation; (ii) no weighted averaging (i.e., multiplying payoffs times probabilities) is required; and, perhaps most importantly, (iii) because the magnitude of the slope in the relationship between A_1 and $A_2|A_1$ is substantially greater than for the linear tradeoff between expected return and reductions in standard deviation.

The slope of $A_2|A_1$ with respect to A_1 is $-\frac{h-r}{r-l}$, which describes the rate of tradeoff between the two aspirations. Every extra dollar, rupee, or unit of wealth by which the decision maker wants to increase the portfolio's lower bound incurs an easy-to-understand cost, namely, the reduction of $\frac{h-r}{r-l}$ in the best-case aspiration. There is another interesting analytic implication that follows from our simple measurement of risk acceptance by satisficing aspirations (with empirical analysis presented subsequently Section 4). The most basic measure of risk acceptance is perhaps the portfolio's risk weighting $\frac{i}{e}$ (measuring the proportion of the portfolio's initial value e allocated to the risky asset i). But $A_2 - A_1 = r(e-i) + hi - r(e-i) - li = (h-l)i$, by Eqs. (1) and (2), which implies $\frac{i}{e} = \frac{h-l}{h-l}\frac{i}{e} = \frac{A_2 - A_1}{(h-l)e}$. In other words, the subject's proportion allocated to risk $\left(\frac{i}{e}\right)$ can alternatively be interpreted as the proportion of the maximal best-to-worst case range ($he - le$) that the subject chooses as his or her portfolio's best-to-worst-case ($A_2 - A_1$). If a subject were unaware of Eq. (3) and undertook to freely choose an "independent" best-case aspiration, then the shaded region in Fig. 1 would represent the "choice set" constraining the feasible range for best-case aspirations and the upper segment of the triangle (given by Eq. (3)) could be regarded as "optimal satisficing" (i.e., the maximal best-case payoff for any given choice of A_1) as is set automatically by the satisficing elicitation tool.

Our elicitation tool focuses on cultivating awareness of the upper segment of the triangle in Fig. 1. In contrast, standard elicitation techniques for risk preferences which follow the EU approach focus on the linear tradeoff between expected value and standard deviation. Relating our satisficing approach to the standard EU approach, we observe that the subject's choice of A_1 maps into mean and variance of the portfolio as follows:

$$E\left[iX + (e-i)r\right] = E\left[\frac{(er - A_1)}{(r-l)}X + \frac{(A_1 - el)}{(r-l)}r\right] = \frac{(er - A_1)}{(r-l)}(pl + (1-p)h) + \frac{(A_1 - el)}{(r-l)}r, \tag{4}$$

$$Var\left[iX + (e-i)r\right] = \left[\frac{(er - A_1)}{(r-l)}(h-l)\right]^2 p(1-p). \tag{5}$$

The square root of Eq. (5) is a decreasing linear function of A_1 with slope $-\frac{(h-l)}{(r-l)}[p(1-p)]^{1/2}$. The expectation and standard deviation of the portfolio's terminal value therefore decrease linearly in A_1. Section 4 investigates willingness to pay for risk reduction using our satisficing approach and risk aversion measured using the standard EU approach. The next section describes the experimental design and data.

3. Experimental data and design

The experiment began by asking subjects to indicate the amount of money that they would typically save or invest in a year. They were later given a chance to modify this decision after learning the probability distributions of the bond and risky asset with which they were asked to choose a portfolio. Therefore, the decision of how much to invest and the portfolio allocation decision can be regarded as a joint decision that would be represented as simultaneous choice if modeled formally. Subjects were instructed to think inclusively so that, at the very minimum, the "savings and investment" number they produce includes bonds, bank deposits and stock market shares, as well as land purchases, tools and other forms of physical capital, in addition to gold which is widely owned in India.[7] A sample of 150 subjects attending financial literacy workshops conducted by the National Institute of Securities Markets (NISM) is the primary data used in this study.[8] By design (and consistent with the NISM's program goals of improving financial literacy across a broad cross-section of Indian society), the subjects in our sample came from socioeconomically diverse backgrounds. The sample includes subjects whose ages and jobs span a relatively broad range, including professionals, students, small business owners and homemakers.

The first piece of information collected was the individual's initial level of full-year savings and investments.[9] Subjects were instructed to think inclusively about their savings and investments. Subjects were described the reward structure of the investment based on which they could change their initial investment to a desired investment e, which was finally binding. The portfolio choice task began by introducing subjects to a computer-based tool for entering different values of, and eventually eliciting a final decision on, an acceptable worst-case portfolio value, A_1.

Unlike standard portfolio choice tasks, the worst-case aspiration A_1 is the subject's primary choice variable in our elicitation technique.[10] The portfolio tool auto-updates other variables relevant for describing the portfolio that are determined by any value entered for A_1. This information (auto-updating as the subject enters different values of A_1) includes: the amount invested in the risky asset i; the amount allocated to bond $e - i$; and the *best-case aspiration* A_2 corresponding to the entered value of A_1.[11] This approach that automatically assigns maximal A_2 conditional on A_1 provides a meaningful measure of optimality following from observations and analysis in Güth (2007). Before elicitation using this *satisficing method*, the protocol asked for a preliminary portfolio choice referred to in Table 1 as investment in the risky asset i chosen by *own method*.

Table 1 provides an outline of the elicitation protocol with mean responses in levels and also normalized by initial portfolio value e.[12] Following Table 1 from top to bottom, subjects first choose the amount to be invested annually in the financial portfolio (e) which is to be allocated across the risk-free bond and risky asset. Next, subjects directly choose the amount (i) to be invested in the risky asset using the subject's *own method*. Then subjects are asked to experiment with the satisficing elicitation tool in which subjects enter A_1 (while values of i, $e - i$ and A_2

[7] A primary cause of poor external validity, even when the sampled individuals are representative of the target population is mismatch between an experimental task and the real-world behavior to which a study aims to generalize (Hershey & Schoemaker, 1985; Pennings & Smidts, 2003). We therefore wrote an experimental protocol that reflects close attention to matching Indian subjects' conception of the full range of investment decisions relevant to their life situation.

[8] NISM is an educational initiative of the Securities and Exchange Board of India (SEBI), which is India's counterpart to the U.S.'s Securities and Exchange Commission, whose responsibilities include both regulatory and educational goals. NISM regularly conducts workshops across India to promote financial literacy.

[9] Many authors, including the US's SEC (https://www.sec.gov/rss/ask_investor_ed/saveinvest.htm), distinguish savings (defined as funds *not at risk*, e.g., bank deposits, government bonds, money market mutual funds) from investments (defined as taking on risk of negative returns to grow wealth). Given real-world uncertainty about real returns on government bonds, money market accounts' "gating" policies and recent history of "breaking the buck," not to mention the bail-in experience of bank depositors in Cyprus, and—of special importance in India—ambiguity about how gold fits with the SEC's definitions of savings (wealth storage) versus investment (expected capital gains), we argue that individual-level savings and investments is the theoretically appropriate pool of investable funds over which allocation decisions into equity versus bonds are typically made.

[10] This deliberate framing of portfolio choice as choosing an acceptable worst-case portfolio value draws on in Güth (2007) and Fellner et al. (2009), whose elicitation allowed subjects to choose either A_1 or A_2.

[11] Screenshots of the interface used to elicit satisficing decisions about A_1 are shown in Appendix 1.

[12] Preliminary survey questions were used to screen for innumeracy and illiteracy with respect to basic finance and investing vocabulary, which eliminated 24 subjects from the beginning pool of 150.

Table 1
Descriptive Statistics, $N = 126$, in INR levels (normalized by e in parentheses below)[a].

Elicitation step #	Variable elicited	Description	Mean	Std. dev	Min	Max
1	Initial amount in the portfolio, e	Amount (in INR) representing one year's savings and investment to be allocated across the bond and risky asset. Empirical distribution of e is shown in Appendix 3.	201,317 (1.00)	258,819 (0.00)	6000 (1.00)	2,000,000 (1.00)
2	Subject's task is to choose amount of INR to be invested, i, in the risky asset using *own method*	Portfolio choice by own method (elicitation without satisficing frame). Given e (initial wealth in INR), this step requires the subject to directly choose an amount of INR to be invested in the risky asset, i. The empirical distribution of relative risk weighting i/e by own method is shown in Appendix 4.	150,849 (0.68)	188,151 (0.23)	6000 (0.15)	2,000,000 (1.00)
3	Subject's task is to choose worst-case aspiration, A_1, thereby determining i and A_2 by the *satisficing method*	Next, subject chooses a worst-case aspiration A_1 for the low-payoff state, which determines $A_2 \| A_1$ and the allocation to the risky asset, i. The empirical distribution of relative risk weighting i/e by satisficing method is shown in Appendix 5.				
	Worst-case aspiration A_1	The minimum low-state payoff that is acceptable	191,465 (0.96)	239,521 (0.05)	5400 (0.90)	1,800,000 (1.07)
	Best-case aspiration $A_2 \| A_1$	The maximum high-state payoff that is feasible for a given worst-case aspiration	255,432 (1.25)	335,098 (0.06)	7920 (1.13)	2,640,000 (1.32)
	Allocation to risky asset i, using satisficing technique	based on satisficing elicitation technique	149,921 (0.68)	236,851 (0.26)	3000 (0.15)	2,000,000 (1.00)
4	Comparison of investment in the risky asset (i) by satisficing versus own method	Subject's choice of i using aspiration satisficing minus subject's choice of i using own method. Appendix 6 reveals substantial variation (not captured by mean contrasts in this table) using a scatterplot of portfolio weights on the risky asset in satisficing versus own methods.	− 929 (− 0.0008)	23,533 (0.13)	− 100,000 (− 0.55)	75,000 (0.33)
5	Subject chooses which portfolio she prefers: aspiration satisficing elicitation versus own method	Percentage preferring satisficing elicitation	84.9%	35.9%	0%	100%

Table 1 presents the steps in the elicitation tool, and the descriptive statistics of various experimental responses that were elicited from subjects, as well as the subject's preference for the satisficing elicitation task.

[a] Scaled values are shown in parentheses. Each subject chose their own total amount to invest in the portfolio, e. To facilitate interpersonal comparisons, we normalize level amounts invested in the risky asset i (chosen directly by own method or indirectly by means of worst-case aspiration A_1) by reporting A_1/e, A_2/e and i/e.

Table 2
Demographic information for sample of 126 subjects.

	Variable	Frequency (out of 126)	Percentage
Gender	Female	29	23.0
	Male	97	77.0
Age	Below 30	72	57.1
	30–40	32	25.4
	40–50	16	12.7
	50–60	5	4.0
	> 60	3	2.4
Academic Qualification	School final	0	0.0
	Graduate	25	19.8
	Post-graduate	44	34.9
	Professional degree	43	34.1
	Ph.D. and above	16	12.7
Dependents	None	57	45.2
	0–2	43	34.1
	3–5	11	8.7
	> 6	16	12.7
Marital status	Unmarried	52	41.3
	Married	74	58.7
Occupation	Salaried	81	64.3
	Business	4	3.2
	Retired	4	3.2
	Professional	16	12.7
	Student/unemployed	21	16.7
Individual income (INR)	Below[a] 100,000	11	8.7
	100,001–500,000	47	37.3
	500,001–1,000,000	40	31.7
	1,000,001–1500,000	17	13.5
	Above 1500,000	10	7.9
Wealth (INR)	Below 1,000,000	93	73.8
	1,000,001–2,500,000	23	18.3
	2,500,001–5000,000	4	3.2
	5000,001–7,500,000	0	0.0
	Above 7,500,000	6	4.8

[a] The Indian convention for placing commas in written numbers is to place the comma after the Lakhs column (hundred thousands column) as well as after the thousands column. The largest income category is written in the Tables in this paper using the US convention as "Above 1500,000," which could be read by an Indian subject as "above 15 lakhs" or, equivalently, as " > 1.5 million INR." Using recent USD/INR exchange rates, 1.5 million INR translates to roughly $100,000 USD.

auto-update) before finally choosing a portfolio by entering final decision about A_1, which we refer to as the *satisficing method*. There is substantial within-person variation across the two methods of elicitation not readily apparent from the similar mean values in Table 1. After all portfolio decisions are submitted, subjects are asked which way of choosing a portfolio they prefer.

Table 2 provides summary statistics about the sample's demographic characteristics. The sample's age distribution covers a wide empirical range, from 22 to 70 years old. Subjects are predominantly male (77%) with more education and larger incomes than is average in India (mean annual salary is approximately INR 750,000).

An example may provide useful illustration. The subject chooses e = INR 100,000 (US$1500) which determines the admissible range for the worst-case portfolio outcome, ranging (riskiest to safest portfolio choices) from INR 90,000 to 110,000. The subject chooses i using the subject's own method, which imposes no constraints on subsequent portfolio choice using the satisficing method. The subject then chooses a portfolio using the satisficing method by entering a value for A_1 (e.g., INR 95,000, which is in the admissible range of INR 90,000 to 110,000). Note that the admissible range is not presented directly to subjects. Instead, feedback is given entering an inadmissible value stating that their worst-case aspiration is inadmissible before being prompted to re-enter a valid value of A_1. Based on e and the worst-case aspiration A_1, the preference elicitation tool computes the levels invested in risky and safe assets, i and e–i, and the best-case aspiration (A_2) implied by the entered value of A_1. Based on $A_1 = 95{,}000$ (i.e., the subject chooses to accept the possibility of a loss of 5000), the implicit portfolio is i = 50,000 in the risky asset and $e-i$ = 50,000 in the risk-free bond, which implies that $A_2 = 126{,}500$ (conditional on A_1).[13]

In other words, risk elicitation by satisficing asks the decision maker to formulate her worst-case aspiration A_1 from the feasible region. This choice (together with e), in turn, determines the feasible range for subjective beliefs about the best-case gross portfolio return, which ranges from 1.1 to the upper bound given by the following decreasing linear function of the worst-case portfolio value: $\frac{A_2}{e} = \left[\frac{1.32-0.9}{1.1-0.9}\right]1.1 - \left[\frac{1.32-1.1}{1.1-0.9}\right]\frac{A_1}{e}$. An arbitrary choice of $\frac{A_2}{e}$ from this feasible interval would, in general, be sub-optimal. Our technique, however, ensures that subjects achieve the best best-case aspiration by automatically assigning the maximal A_2 conditional on A_1 given by the linear formula above, therefore, providing a meaningful measure of optimality following from Güth's (2007) analysis that allows for sub-optimal aspirations. In our previous example where A_1 = INR 95000 and the feasible range for A_2 is (INR 110,000, INR 126,500), any choice of A_2 below INR 126,500 is wasteful in the sense that there are feasible higher-payoff aspirations consistent with the decision maker's low-payoff aspiration.

We acknowledge a potential semantic conflict with authors who define satisficing such that it cannot be optimal or in contexts in which no optimal choice rule exists (e.g., Gigerenzer's interpretation of satisficing as being simple and smart in environments where optimization has no solution or is intractable). Our elicitation method leverages the simplicity of a small world in which risk is characterized by known probability distributions to elicit information about risk preferences when portfolio outcomes are framed as decisions about worst-case and best-case portfolio values. We argue that our approach draws inspiration from Simon (1972) regarding the possibility of harmonizing satisficing and optimizing as decision procedures:

> "A satisficing decision procedure can be often turned into a procedure for optimizing by introducing a rule for optimal amount of search, or, what amounts to the same thing, a rule for fixing the aspiration level optimally."
>
> (Simon, 1972, p. 170)

Table 1 shows the elicitation steps and descriptive statistics of elicited values in the sample of 126 subjects. Table 1 reports the mean, standard deviation, minimum and maximum values for initial portfolio value (e), for subject's choice of risky investment using *own method*, elicitation of worst-case aspiration A_1 that implies the best-case aspiration $A_2|A_1$ and implicit choice of allocation in the risky asset (i) using *satisficing method*. Table 1 also gives a comparison of portfolio allocations to the risky asset by *own method* versus aspiration *satisficing method*.

The raw elicitation of aspirational outcomes is in units of INR. These responses are re-scaled onto unit interval by dividing each subject's aspirational pair by the desired investment amount (e). Table 1 shows the mean value of the rescaled worst-case aspirations is 0.96, which implies that subjects are, on average, 30% $\left[\frac{(0.96-0.90)}{(1.10-0.90)}\right]$ away from the maximum risk (0.90 or −10%), and 70% away from minimum risk (1.1 or +10%).

Before the subject is introduced to the satisficing task in the experiment, she is asked to choose the asset allocation based on her own method. *Own method* means that she chooses i directly and the balance ($e-i$) is allocated to the risk-free asset. Then, the subject is familiarized with using the aspiration-satisficing elicitation technique instead of selecting i directly for forming the portfolio. The subject's task in the aspiration-satisficing elicitation technique is to choose A_1, which

[13] Our approach follows that of Fellner et al. (2009). Our approach differs, however, in that the decision maker chooses A_1 and the tool automatically selects the maximal A_2 such that the aspiration pair maximizes the expected payoffs ("optimal satisficing") conditional on the choice of A_1 (cf., Bearden & Connolly, 2008; Güth, 2010; Schwartz, Ben-Haim, & Dasco, 2011).

determines the portfolio parameters i and $e-i$. Once the subject is satisfied with the allocation, she is asked to choose one of the two portfolios, effectively stating whether she prefers the direct-method elicitation of i or the indirect aspiration-satisficing-elicitation portfolio. The data reveal that 84.9% of the subjects preferred the allocation based on the satisficing approach rather than directly choosing i.

Although our data do not constitute direct evidence about the decision process that subjects used in making their respective portfolio choices, our exit-survey responses strongly suggest that the satisficing technique caused the decision maker to reflect on a natural risk-return tradeoff using an easy-to-understand question regarding minimum payoffs, worst-case payoffs or low-state returns. Our elicitation tool appears to simplify the portfolio choice task, which would seem to help ensure that the decision outcomes are associated with genuine aspiration levels. The expressed preference—strongly in favor of portfolios elicited using satisficing over own method—is another reason why we believe our elicitation technique using satisficing of aspirations should be considered. Future work comparing elicitation methods would benefit from counterbalancing and/or randomizing the order of elicitation methods to test whether subjects' expressed preference for satisficing portfolios is confounded by serial ordering of these methods.

Prior investigations by Fellner, Güth, and Martin (2006) and Güth, Levati, and Ploner (2008) expound the view that satisficing is sensible, more descriptively realistic and generalizable across a broad range of decision domains. A related study shows that decision makers prefer satisficing as a decision process in the particular domain of price competition (Güth, Levati, & Ploner, 2012). Bhaskaran, Parihar, and Prakhya (2008) report that satisficing remains as the preferred decision making approach as the size of the choice increases. Many models of satisficing eschew probabilities and instead use aspiration levels based on the justification that they are simple and therefore easy to understand (Brown & Sim, 2009).

In our view, the artificially simple portfolio choice task combined with worst-case aspiration framing significantly simplifies portfolio choice and therefore reveals new information about risk preferences that more standard measures are unlikely to record. Setting aspirations simplifies the search process through an infinite set of pairs of expected return and risk in the standard model of portfolio choice. Our tool enables users to choose a portfolio and thereby express a risk preference simply by choosing a worst-case portfolio value A_1 below which the portfolio's terminal value cannot fall. Choosing a worst-case aspiration that bounds terminal portfolio values, the role of satisficing in our approach can be described intuitively as limiting losses and then working backwards to identify a portfolio allocation that guarantees the loss limit is respected. We show how portfolio choice induced by this framing in terms of worst-case aspirations provides analytic and numerically relevant measures of risk aversion using standard functional forms: *constant absolute risk aversion* (CARA) and *constant relative risk aversion* (CRRA) expected utility functions.

4. Analysis: satisficing and risk aversion

Previous studies by Fellner et al. (2009) and Güth (2010) propose that satisficing aspirations may provide a more natural way of defining and eliciting risk attitudes. When considering new ways to define and measure risk attitudes using satisficing aspirations in our setup, one might define risk aversion in terms of how conservatively the subject chooses A_1. Alternative measures of risk acceptance could also be based on the difference, $A_2 - A_1$, or the ratio, A_2/A_1.

Under the assumption that the subject is an expected utility maximizer, a risk-aversion measure can be computed analytically for both CARA and CRRA utility functions. We provide analysis for those calculations and then report risk aversion measures corresponding first to CARA and then CRRA and compare distributions of risk aversion estimates based on CARA and CRRA.

In the expected utility approach, the decision-maker has complete information about the states of nature and their associated probabilities. (See Fellner et al., 2006, for more on optimal portfolio choice in relation to satisficing). Satisficing is such that the decision-maker fixes an aspiration level and chooses the first action along a sequential search path which meets that aspiration (Simon, 1957; Selten, 1998). In contrast, in the case of optimization, the decision maker considers the entire space of outcomes and associated payoffs to identify the optimal choice. In our satisficing approach, however, the decision maker fixes a min-max aspiration pair that limits losses and bounds the portfolio's terminal value.

4.1. Satisficing and CARA expected utility

The constant absolute risk aversion (CARA) function can be defined as:

$$u(x) = 1 - e^{-kx}, \tag{6}$$

where x denotes wealth and k is the coefficient of absolute risk aversion. For investment decisions allocating i to the risky asset and $e-i$ to risk-free bonds, expected utility is:

$$\begin{aligned} u(i) &= p\{1 - e^{-k[r(e-i)+li]}\} + (1-p)\{1 - e^{-k[r(e-i)+hi]}\} \\ &= p\{1 - e^{-kA_1}\} + (1-p)\{1 - e^{-kA_2}\} \end{aligned} \tag{7}$$

The calculation above uses the substitutions $r(e-i) + li = A_1$ and $r(e-i) + hi = A_2$. The experimental design uses $p = 0.5$ for simplicity.

Maximizing $u(i)$ with respect to i at an interior solution satisfies the first-order condition $u'(i) = 0$. Assuming this first-order condition is satisfied, we use each subject's worst-case aspiration to compute i and, based on that value, to compute the value of k that describes the utility function that is maximized by the subject's observed choice of A_1 (assuming some risk taking, $A_2 > A_1$):

$$\begin{aligned} k &= \left\{\frac{\log[(1-p)(h-r)] - \log[(r-l)p]}{(h-l)i}\right\} \\ &= \left\{\frac{\log[(1-p)(h-r)] - \log[(r-l)p]}{A_2 - A_1}\right\} = \\ &\left\{\frac{\log[(1-p)(h-r)] - \log[(r-l)p]}{(h-l)(er-A_1)}\right\}(r-l). \end{aligned} \tag{8}$$

Eq. (8) provides a direct relationship between the risk-aversion parameter k and worst-case aspiration A_1. All else equal, greater A_1 (which reduces i and the difference $A_2 - A_1$) implies greater risk aversion. This measure of risk aversion, of course, is dependent on the size of the investment e and currency units used.

The implication of setting aspiration compared to standard rational choice with CARA preferences is illustrated in Fig. 2. In Fig. 2, a satisficing portfolio is shown with its associated expected utility value and, using Eq. (8), the value of k for which an expected utility maximize with CARA preferences would have optimally chosen the same portfolio.

The expected utility for the most risky form of lottery (el, eh), is utility associated with the midpoint C on the straight-line segment AB. For Aspiration lottery $(A_1, A_2|A_1)$ where A_1 is greater than el (and hence $A_2|A_1$ is less than eh), utilities at A_1 and A_2 are given by the heights of the points A' and B', respectively and the expected utility from the lottery, $Eu(x)_A$, is the utility associated with the midpoint C'. The expected utility for the least risky or rather the risk-free form of lottery (er, er) is labeled as $u(x)_{safe}$ in Fig. 2.

An individual who wants no risk will opt for investing only in the bond and an aspiration portfolio (er, er) while the riskiest option of investing only in the risky asset is associated with the aspirations(el, eh). The line $L'L''$ in Fig. 3 depicts the range of possible aspiration portfolios written in the space of standard deviation on the x-axis and expected return on the y-axis. The segment in Fig. 3 is the choice set (assuming that short selling of either asset is not allowed) and the slope of the line

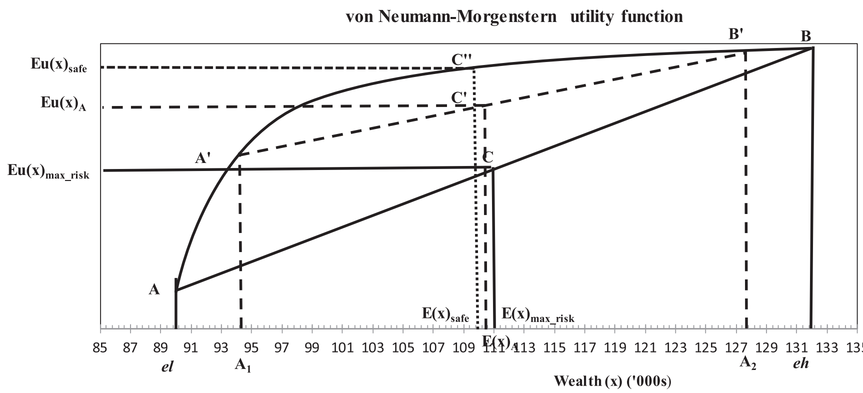

Fig. 2. Illustration of satisficing aspirations that can be made consistent with expected utility maximization for an appropriately chosen parametric value of absolute risk aversion k, relative risk aversion 1-α or appropriately concave utility function.

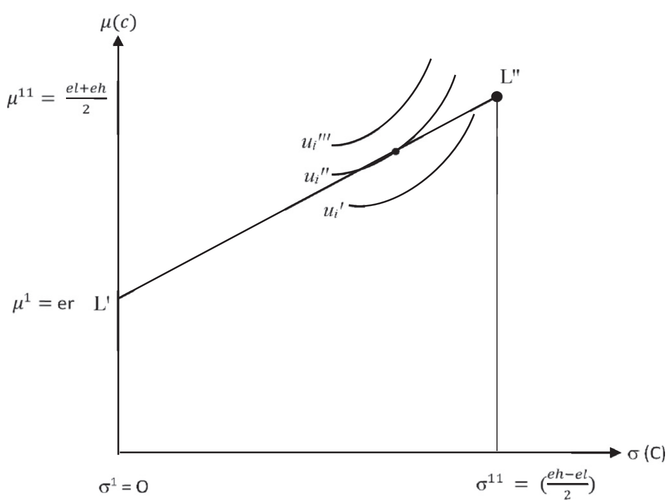

Fig. 3. Best-case versus worst-case aspirations translated to the standard risk-return-space view from introductory finance.

is the price of risk. An individual i whose CARA risk aversion is k_i, is represented by indifference curves labeled in Fig. 3 as u_i^I, u_i^{II}, $u_i^{III}$and her optimal choice when faced with the opportunities that the market offers is the combination of mean and standard deviation associated with the worst-case aspiration A_{1i}.

4.2. Satisficing and CRRA expected utility

A similar correspondence will hold in the case of a CRRA utility function $u(x) = x^{\alpha}$, $\alpha > 0$. Expected utility is given by the formula $E[u(iX + (e - i)r)] = (1 - p)(A_2)^{\alpha} + p(A_1)^{\alpha}$. Assuming the first-order condition for A_1 holds and solving for α provides the following person-specific measure of risk aversion using the RRA formula:

$$1 - \alpha_i = log\{[(h - r)/(r - l)][(1 - p)/p]\}/log\,[A_2/A_1]. \tag{9}$$

4.3. Is there new information about risk preferences in the empirical distributions of implicit risk aversion elicited by satisficing aspirations?

Fig. 4 shows empirical distributions of k_i and $1 - \alpha_i$. The shapes of these distributions are substantially different. For CARA preferences, a unique value of k is associated with each distinct aspiration A_1. For CRRA preferences, a unique value of α is associated with each distinct value of the elicited proportion i/e (i.e., the subject's implicitly chosen portfolio weight on the risky asset). The empirical distributions in Fig. 4 describe the sample variation observed in our sample's risk acceptance as filtered through the respective assumptions of EU under CARA and CRRA utility functions as specified above. With CARA preferences, the sample frequencies clustered within a particular band of values of k_i reflect individuals with the same worst-case aspiration regardless of their chosen investment level e_i. In the empirical distribution corresponding to the assumption of the CRRA utility function, sample frequencies clustered within a particular band of values of $1 - \alpha_i$ reflect individuals with similar worst-case aspirations relative to chosen investment levels e_i.

One important stream in the risk preference literature explored the link between demographics and risk preferences (Riley and Riley & Chow, 1992; Hartog, Ferrer-i-Carbonell, & Jonker, 2002; Weber, Blais, & Betz, 2002; Dohmen et al., 2011). Table 3 presents regressions of five dependent variables[14] measuring risk acceptance as functions of wealth, income, and other demographic information. These five dependent variables providing alternative measures of risk acceptance are: risky investment level i; portfolio risk weighting $\frac{i}{e}$ which is the same as the subject's chosen best-to-worst-case range as a percentage of the theoretical maximum possible range; the subject's chosen percentage increase in best/worst ratio with respect to its theoretical minimum of unity as a percentage of maximum possible percentage increase over unity, $\left(\frac{A_2}{A_1} - 1\right)\Big/\left[e\left(\frac{1.32}{.9} - 1\right)\right]$; inverse CARA risk aversion (which translates to risk acceptance) logged to make the asymmetric distribution of k more symmetric, $-\log(k)$; and inverse CRRA risk aversion, 1 − α. According to the results in Table 3, those in the very top income bracket tend to have greater risk acceptance as measured by i and $-\log(k)$, but not the other level-independent measures of risk acceptance. Married status is negatively associated with all risk acceptance measures with statistical significance in those two level-sensitive measures of risk acceptance in Table 3. Table 3 shows that the information elicited by satisficing aspirations is not trivially explainable in terms of, or multicollinear with, the demographic information in our sample. We interpret these results as potentially fertile ground for future work to investigate the predictive power of information contained in these alternative transformations of aspiration satisficing which we have shown are theoretically rationalizable measures of risk acceptance. We interpret these results as indicative of the potential for future work investigating the predictive power of information contained in these alternative transformations of aspiration satisficing which we have shown are theoretically rationalizable measures of risk acceptance.

We speculate that satisficing aspirations as a means of making high-stakes investment decisions (ranging from retirement portfolio choice to airlines' investment and cost-risk-hedging strategies) can function as a smart heuristic that effectively reduces variance. Coricelli, Diecidue, and Zaffuto (2016) find that aspiration levels can be used to predict choices, and the resulting choice patterns characterize a heuristic for

[14] The unconditional empirical distributions for these dependent variables, which provide alternative measures of risk acceptance, are reported in Appendix 2. The simple correlation between i and e is positive (0.96) and statistically significant.

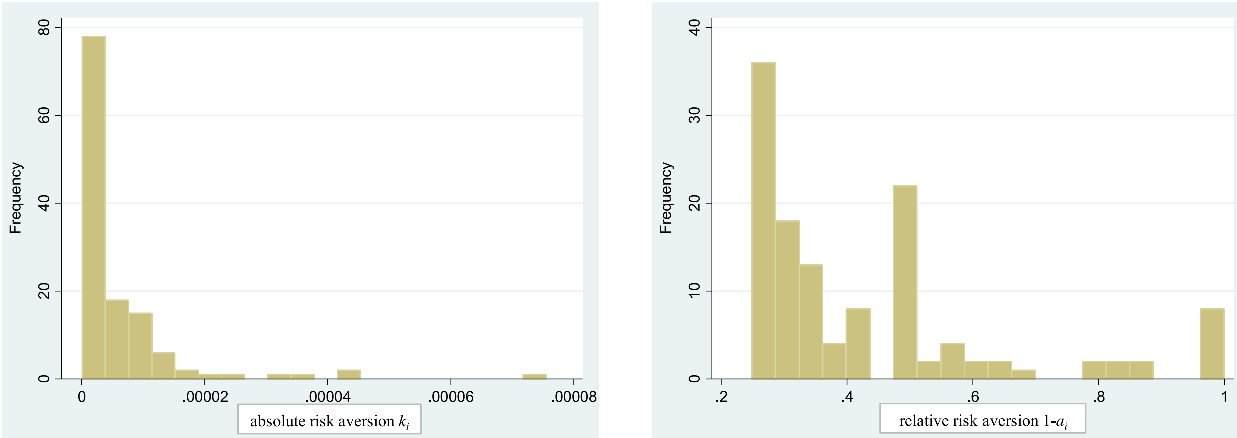

Fig. 4. Empirical distributions of absolute risk aversion *ki* assuming CARA preferences and relative risk aversion 1-*ai* assuming CRRA risk preferences, $N = 126$.

reducing the complexity of risky decisions. Aspiration setting and satisficing frames the decision about acceptable lower-tail risk as the choice variable to be traded off against upside gains. The simple analytic work and very preliminary empirical investigation reported here should serve to demonstrate strong links between satisficing as risk-hedging and orthodox measures of risk-aversion in the expected utility framework which were previously unrecognized. The satisficing scheme is an expression of risk aversion in the sense that it prompts consideration of a fundamental tradeoff by which improving lower-tail risk comes at the cost of reducing upside gains.

5. Satisficing approach and aspiration setting

Simon's bounded rationality research program (variously interpreted in the psychology and economics and judgment and decision making literatures) undertakes to describe how people actually make decisions in an uncertain world with limited time, information and cognitive resources. *Satisficing* is one such decision process, selecting good-enough outcomes that are representable as threshold conditions (as inequalities rather than the first-order conditions typically used to characterize decision rules derived under the assumption of constrained optimization). Satisficing may enable the decision maker to economize on time, memory or cognitive effort by prescribing partial rather than exhaustive search of the choice space. The good-enough outcome described by a satisfier's stopping rule satisfies one or more essential criteria while advantageously sacrificing less consequential or superfluous ones. Schmidtz (2004, p. 30) describes satisficing as a "humanly rational strategy." Selten (1998) views satisficing as a search process in which preferences may be expressed as goals or aspirations.

Simon (1959) proposes that conditions for satisficing specified by aspiration levels are analogous to formulating a target. In the context of risk preferences and determinants of risky choice, some researchers assert that many people's psychological conception of risk (including both non-experts and experienced business owners) is primarily a consideration of the prospect of not meeting a target, which can be interpreted as the possibility of a loss (Bordley & Kirkwood, 2004; Bordley & LiCalzi, 2000). There is also evidence that managers conceive of their goals as target rates of return (Lanzillotti, 1958; Shipley, 1981) and tend to disregard investment possibilities that are likely to underperform relative to their target (Payne, Laughhunn, & Crum, 1980). Evidence also suggests that many firms do not seek to maximize profit but rather to achieve good-enough levels of profit (e.g., greater than a minimally acceptable target). Furthermore, organizations may consider problems as resolved when a good-enough solution has been found (Choo, 1998). Brown and Sim (2009) introduce a class of satisficing measures for evaluating the quality of financial positions based on their ability to achieve desired financial goals. Risk management techniques, such as, Roy's (1952) safety-first criterion, can be represented mathematically as minimizing the probability of a bad-state outcome, namely, requiring that the probability that the portfolio's return falls below a minimum desired threshold is as small as possible. These papers suggest that aspiration setting in the context of satisficing may provide a more natural way of characterizing an important set of real-world decision makers' attitudes toward risk.

We believe that future research could shed new light on the extent to which real-world organizations set positive aspirations (e.g., sales target, occupancy rate, graduation rate, and rate of return) versus worst-case aspirations which may follow naturally from regulatory constraints or those imposed by creditors. It remains an open question the empirical distributions of entrepreneurs' use of maxima versus minima in formulating their key objectives. Directions for future research on the elicitation of risk preferences by means of satisficing—in the context of organizational behavior and the theory of the firm—-would include questions such as: How do money managers and individual investors decide to exit from an investment (e.g., taking profits or as stop-loss thresholds)?; How do finance managers set hurdle rates for new investment projects?; and How do start-ups choose which equity stake to offer to outside investors.

A broad range of empirical applications provide both descriptive and normative support for satisficing models. Lant (1992) investigates organization goals and finds that aspiration levels provide the most robust and veridical description of organizational goal setting. Artinger and Gigerenzer (2012) report that a majority of used car dealers follow pricing strategies based on principles of aspiration adaptation rather than optimization rules equating marginal benefits and marginal costs. Hu, Blettner, and Bettis (2011) show that dynamic adaptation of aspiration levels can lead to superior firm performance in terms of greater terminal wealth. Aspiration-based satisficing simplifies the decision process by ending the search for alternatives as soon as an alternative exceeds the aspiration level (Berninghaus, Güth, Levati, & Qiu, 2011; Güth, 2010).

In contrast to satisficing, the decision process of constrained optimization requires substantially greater computational power, memory and time, and may not be tractable or computable (Todd & Gigerenzer, 2003; Vriend, 1996). The fast and frugal heuristics program initiated by Gigerenzer, Todd, and The ABC Research Group (1999) *Simple Heuristics That Make Us Smart* focuses on simple decision rules that require substantially less information and take advantage of ignorance and the benefits of deliberately ignoring payoff-relevant predictors in particular classes of environments (Woike, Hoffrage, & Petty, 2015; also see Berg & Hoffrage's, 2008, model of rational ignoring with unbounded cognitive constraints).

Table 3
Regressions of five dependent variables measuring risk acceptance (*t* statistics in brackets [.] below each estimated coefficient).

Dependent variable	Investment level *i* in risky asset			Portfolio weighting[a] on risk *i*/e			ratio_relative_aspiration_spread ($A_2/A_1 - 1$) / ($e*(1.32 / 0.9 - 1)$)			− log(ARAk), where CARA ARAk is computed using Eq. (8)			RRA = 1-α, where CRRA RRA α is computed using Eq. (9)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	basic	+ income	+ alldemog	basic	+ income	+ alldemog	basic	+ income	+ alldemog	basic	+ income	+ alldemog	basic	+ income	+ alldemog
Variables															
Logwealth	66,996	36,281	53,480	0.0309	0.0185	0.0387	0.0338	0.0197	0.0400	0.264	0.0251	0.125	0.0159	0.0104	0.0308
	[3.027]	[1.517]	[2.053]	[1.250]	[0.666]	[1.268]	[1.295]	[0.674]	[1.240]	[2.341]	[0.215]	[0.992]	[0.781]	[0.457]	[1.225]
inc1to5Lakh		− 39,014	10,583		− 0.0480	− 0.0252		− 0.0419	− 0.0205		− 0.225	0.0271		− 0.0760	− 0.0424
		[− 0.539]	[0.140]		[− 0.571]	[− 0.284]		[− 0.474]	[− 0.219]		[− 0.638]	[0.0736]		[− 1.102]	[− 0.579]
inc5to10Lakh		39,803	70,354		− 0.00598	0.00412		0.00257	0.0116		0.576	0.725		− 0.0437	− 0.0249
		[0.537]	[0.915]		[− 0.0696]	[0.0457]		[0.0284]	[0.122]		[1.594]	[1.942]		[− 0.620]	[− 0.335]
inc10to15Lakh		37,308	69,431		− 0.0330	− 0.00135		− 0.0229	0.00990		0.717	0.822		− 0.0801	− 0.0519
		[0.439]	[0.811]		[− 0.335]	[− 0.0135]		[− 0.220]	[0.0935]		[1.731]	[1.980]		[− 0.990]	[− 0.627]
inc15Lakh_or_more		258,500	319,523		0.0765	0.132		0.0984	0.153		1.573	1.872		− 0.0179	0.0450
		[2.450]	[2.862]		[0.625]	[1.012]		[0.763]	[1.112]		[3.057]	[3.456]		[− 0.178]	[0.417]
Female			49,504			− 0.0620			− 0.0643			− 0.193			− 0.0394
			[1.029]			[− 1.099]			[− 1.082]			[− 0.826]			[− 0.848]
married_ever			− 117,872			− 0.0982			− 0.102			− 0.513			− 0.0731
			[− 2.355]			[− 1.674]			[− 1.654]			[− 2.110]			[− 1.511]
age30to39			− 25,528			0.0316			0.0352			− 0.160			0.0164
			[− 0.468]			[0.495]			[0.522]			[− 0.604]			[0.312]
age40to49			28,474			0.101			0.113			− 0.0482			0.0195
			[0.386]			[1.162]			[1.244]			[− 0.135]			[0.273]
age50andabove			102,508			− 0.0127			− 0.00982			0.336			− 0.0255
			[1.191]			[− 0.126]			[− 0.0923]			[0.804]			[− 0.307]
Postgrad			53,011			0.0535			0.0546			0.289			0.0587
			[0.679]			[0.584]			[0.566]			[0.762]			[0.778]
prof_degree			35,407			0.0226			0.0213			− 0.0445			0.0428
			[0.514]			[0.280]			[0.250]			[− 0.133]			[0.643]
phd			− 9804			− 0.0569			− 0.0599			− 0.0966			− 0.0327
			[− 0.142]			[− 0.703]			[− 0.703]			[− 0.289]			[− 0.492]
Constant	− 762,043	− 364,112	− 596,384	0.262	0.451	0.214	0.192	0.396	0.161	9.124	12.07	10.91	0.352	0.482	0.212
	[− 2.523]	[− 1.114]	[− 1.698]	[0.775]	[1.189]	[0.520]	[0.540]	[0.991]	[0.371]	[5.932]	[7.575]	[6.399]	[1.270]	[1.548]	[0.625]
Observations	126	126	126	126	126	126	126	126	126	126	126	126	126	126	126
R-squared	0.069	0.146	0.228	0.012	0.026	0.100	0.013	0.028	0.100	0.042	0.195	0.279	0.005	0.019	0.088

[a] The portfolio weight on risk *i*/e is identical to the percentage of maximum possible best-to-worst-case range chosen by subject for his or her portfolio's best-to-worst-case range A_2–A_1, alternatively referred to as diff_relative_aspiration_spread ($A_2 - A_1$) / [$e*(1.32 - 0.9)$].

6. Conclusion

The focus of our study was to introduce a new technique for eliciting risk preferences based on satisficing in the context of portfolio selection. We demonstrated analytic and empirical links between satisficing and risk aversion (using the EU approach) that, to our knowledge, have not been reported before. Aspirations are elicited by asking subjects to set bounds on worst-case and best-state realized values of their portfolio. Directly choosing the worst-case portfolio outcome provides an intuitive and direct method for revealing risk preferences. We show analytically that choice of the portfolio's worst-case outcome is equivalent to revealing a risk-aversion parameter under the assumption of a particular expected utility function.

The portfolio-choice task that we use requires simple allocation levels of currency to a risky and risk-free asset. The binary risky asset is not as limiting as one might first imagine. Choosing an acceptable worst-case portfolio outcome from a continuum of binary gambles can be interpreted as extending more broadly to real-world assets with continuously distributed payoffs (i.e., where random payoffs are unbounded). The required modification is that the decision variable becomes choosing an acceptable pair of tail risks.

An important advantage of satisficing aspirations as an elicitation technique is its user-friendliness in terms of intuitively matching the units of measure and mental process that both non-experts and experts frequently use to reason about risk. The EU approach requires that subjects exhaustively scan the event space to compute probability-weighted average utilities. In contrast, our technique which uses satisficing to elicit risk preferences may provide a better match with many investors' actual mental process, based on the extent to which the subjects in our sample prefer to think directly about permitting worse worst-case outcomes traded off in favor of better best-case outcomes. Moreover, a large majority of subjects in our sample expressed a preference for the portfolio that was elicited from them by satisficing aspirations over the portfolio chosen using their own method to directly choose an investment level in the risky asset.

The satisficing elicitation technique provides an advantageous framing that gives subjects direct control over the worst-case aspiration—the minimum portfolio value in the event that the risky asset's low payoff realized—as their primary decision variable. We show analytically that the portfolio choice problem of selecting from the continuum of possible binary gambles can be equivalently re-parameterized as either: (i) choosing the gamble that offers the minimally acceptable worst-case payoff; or (ii) choosing the gamble that offers the most preferred mean-variance pair assuming an appropriately chosen utility function and risk-aversion parameter.

In the simplified case of choosing from a continuum of binary portfolios, worst-case outcomes which occur with strictly positive probability are chosen directly. In contrast, in the case of risky assets with infinite state spaces, the worst-case aspiration could be defined as an acceptably small probability on an exogenously given lower-tail event or, alternatively, the threshold that defines an acceptable lower-tail event occurring with an exogenously given lower-tail probability. In the case of continuous state spaces, realized portfolio values lower than the low aspiration level cannot be ruled out, although their probability of occurring can be controlled. The continuous case may require a second decision stage of choosing upper-tail thresholds used to compute tradeoffs measuring how much upper-tail potential is forgone to reduce lower-tail risk by, for example, one percentage point.

Our elicitation technique invites the decision maker to confront risk-reward tradeoffs inherent in many real-world decisions. The design of our elicitation procedure benefits from simplicity, which helps participants easily understand the decision tasks and reason about this important economic tradeoff as an algebraic constraint. The elicited worst-case aspiration maps directly into a maximum return from the investment, which can be interpreted as a best-case aspiration consistent with the worst-case aspiration, as well as portfolio allocations to the risky and risk-free assets.

Despite apparent methodological conflict between satisficing and expected utility maximization, we show that the intuitive elicitation of satisficing aspirations maps into an expected-utility-maximizing portfolio choice for an appropriately chosen risk-aversion parameter. Diecidue and Van De Ven (2008) develop a model that combines aspiration level (simplifying strategy) with expected utility (which is compensatory) and find that the hybrid model is mathematically equivalent to expected utility with discontinuities. Satisficing and EU maximization are indeed distinct mental models. Asking subjects to focus solely on the worst-case outcome when choosing an investment portfolio has potentially important links to the literature on fast-and-frugal trees, motivated by the observation that logically equivalent re-descriptions of probability distributions as natural frequencies, which would include financial payoff distributions, can induce systematically different patterns of choice (Woike, Hoffrage, & Martignon, 2017). The links we demonstrate between satisficing and EU theory are not intended to elide these distinct mental processes. We show, however, that in the small-world problem of allocating wealth across a binary risky asset and a risk-free bond, there is an analytic equivalence that, to our knowledge, has not been reported before and which some may find surprising. The findings in our study largely support those of Van Witteloostuijn (1988) and Güth (2010) which demonstrate that maximizing and satisficing can (in some cases) lead to an identical prescriptive theory regarding portfolio choice. Our simple equivalence result is complementary with the equivalence of satisficing and optimal search in Malakhov (2014).

One promising extension would be to examine the satisficing process under contrasting informational structures as in Papi's (2012) observable versus unobservable cases. Other possibilities would include allowing subjects to experiment with either A_1 or A_2 (while the online tool auto-completes the implied values of A_2 or A_1, respectively). Subjects could then reveal a preference for adjusting worst-case or best-case aspirations. Further tests showing how risk preferences elicited in this way might be affected by treatments introducing additional gain versus loss framing could, for example, provide new links between the information generated by our satisficing elicitation tool and the large behavioral economics literatures on loss aversion and reference-point-dependent preferences.

7. Relevance to business world

One direct application is financial advising. Financial advisors make frequent use of expected utility theory, for example, using a series of questions measuring rates of tradeoff between expected return and risk as measured by standard deviation of annual returns. Customer responses to such questions lead to an estimated value of the client's risk-aversion parameter, which is then used to advise clients how to allocate their financial portfolio (e.g., across “safe” bonds and “risky” equities). Instead of eliciting the risk-aversion parameter directly (based on standard instruments for measuring risk preferences used in finance and experimental economics), our theoretical and empirical results both imply potential to create greater client satisfaction by instead (or additionally) using our technique for risk elicitation and portfolio choice. By encouraging those who seek financial advice to deliberate about worst-case outcomes and make explicit tradeoffs between better worst-case terminal values of their portfolio versus expected returns, our empirical finding that subjects preferred their satisficing portfolios suggests that financial advisors could add meaningful value by interacting with their clients and changing their elicitation protocols in this way. Satisficing techniques could also be prove useful in decisions about how much insurance a firm or an individual should purchase (e.g., re-insurance purchases by US firms that directly provide employees with healthcare and are therefore self-insured, while also seeking to limit losses from catastrophic events for which re-insurance coverage provides coverage once individual or group expenditure thresholds are triggered).

Examples mentioned already in which firms across a broad range of industries, from airlines to agriculture (Lopes, 1987; Lucier, 2004), adopt a strategy of focusing on one decision variable (or a small number of variables)—for example, hedging an airline's future fuel costs, or protecting a farm against losses with satisficing land-use decisions—-reveal that many firms already use satisficing to their advantage. Our main result shows that such satisficing behavior among business owners and management can be interpreted as being perfectly consistent with expected utility maximization. In light of this theoretical result, we believe that, at the very least, management teams that are already inclined to make important decisions by trading off improvements in worst-case outcomes against reductions in expected rates of profits should be encouraged. Satisficing behavior can be both economic *and* behavioral—and, most importantly, profitable. Managers who satisfice should not be told by economists that, because they are satisficing, their decision-making process is therefore sub-optimal, compromised, or second-best.

In unstable environments where the data-generating-process is buffeted by unpredictable shocks, it may be more advantageous by general fitness criteria for organisms to satisfice with respect to a few important variables (e.g., caloric intake, water availability, and protection from predators) rather than devising a "brittle" optimization rule conditioning on a larger vector of observable characteristics whose stochastic structure may catastrophically shift (Bookstaber & Langsam, 1985). Normative arguments in favor of ecological rather than axiomatic rationality and the prescriptive benefits of satisficing are extensive (Berg, 2003; Berg, 2014a; Berg & Gigerenzer, 2007, 2010; Gigerenzer & Selten, 2001).

Caplin, Dean, and Martin (2011) report evidence of frequent satisficing behavior relative to frequencies of other decision processes when facing variable sizes of choice sets and degrees of complexity in the reward–generating environment. By explicitly analyzing complex choice rules, Salant (2011) shows it may be optimal for individuals to switch to a decision rule that is simpler than the rational decision rule. Berg (2014b) reports evidence showing that successful business owners use satisficing (rather than optimization) to choose locations. de Boer, Gaytan, and Arroyo (2006) present an outsourcing model that explicitly incorporates satisficing principles for realistic decision guidance in outsourcing processes while selecting a supplier, project completion, and supplier management. Brighton (2011) argues that, in medical decision-making tasks, satisficing rules that ignore information are easier to use and, at the same time, provide more reliable out-of-sample prediction that are useful in many applied business contexts (i.e. better accuracy than predictions based on more complex, information-intensive optimization models). Various forms of satisficing can be interpreted as fast and frugal decision heuristics that employ easily-computable stopping rules to make adaptive choices across a wide range of real-world environments (Bendor, Kumar, & Siegel, 2009; Gigerenzer, Todd, and The ABC Research Group, 1999). The details of our protocol for eliciting risk preferences by satisficing can be applied directly to financial advising, insurance decisions, and perhaps adapted to reveal actionable new information about managers' strategic thinking in other contexts with links to portfolio choice, insurance and beyond.

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Appendix A. Supplementary data

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References

Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: critique des postulats et axiomes de l'école américaine. *Econometrica,* 503–546.

Artinger, F., & Gigerenzer, G. (2012). *Pricing in an uncertain market* (Working Paper)Max Planck Institute for Human Development.

Barron, G., & Erev, I. (2003). Small feedback-based decisions and their limited correspondence to description-based decisions. *Journal of Behavioral Decision Making, 16*(3), 215–233.

Bearden, J. N., & Connolly, T. (2008). On optimal satisficing: How simple policies can achieve excellent results. *Decision modeling and behavior in complex and uncertain environments* (pp. 79–97). New York: Springer.

Bell, D. E. (1985). Disappointment in decision making under uncertainty. *Operations Research, 33*(1), 1–27.

Bendor, J. B., Kumar, S., & Siegel, D. A. (2009). Satisficing: A 'pretty good' heuristic. *The BE Journal of Theoretical Economics, 9*(1).

Berg, N. (2003). Normative behavioral economics. *Journal of Socio-Economics, 32*(4), 411–427.

Berg, N. (2014a). The consistency and ecological rationality approaches to normative bounded rationality. *Journal of Economic Methodology, 21*(4), 375–395.

Berg, N. (2014b). Success from satisficing and imitation: Entrepreneurs' location choice and implications of heuristics for local economic development. *Journal of Business Research, 67*(8), 1700–1709.

Berg, N., & Gigerenzer, G. (2007). Psychology implies paternalism? Bounded rationality may reduce the rationale to regulate risk-taking. *Social Choice and Welfare, 28*(2), 337–359.

Berg, N., & Gigerenzer, G. (2010). As-if behavioral economics: Neoclassical economics in disguise? *History of Economic Ideas, 18*(1), 133–166.

Berg, N., & Hoffrage, U. (2008). Rational ignoring with unbounded cognitive capacity. *Journal of Economic Psychology, 29*, 792–809.

Berninghaus, S., Güth, W., Levati, M. V., & Qiu, J. (2011). Satisficing search versus aspiration adaptation in sales competition: Experimental evidence. *International Journal of Game Theory, 40*(1), 179–198.

Bhaskaran, A., Parihar, R., & Prakhya, S. (2008). Approaches to decision making under uncertainty. *IIMB Management Review, 20*(2), 228–239.

de Boer, L., Gaytan, J., & Arroyo, P. (2006). A satisficing model of outsourcing. *Supply Chain Management: An International Journal, 11*(5), 444–455.

Bookstaber, R., & Langsam, J. (1985). On the optimality of coarse behavior rules. *Journal of Theoretical Biology, 116*, 161–193.

Bordley, R., & LiCalzi, M. (2000). Decision analysis using targets instead of utility functions. *Decisions in Economics and Finance, 23*(1), 53–74.

Bordley, R. F., & Kirkwood, C. W. (2004). Multiattribute preference analysis with performance targets. *Operations Research, 52*(6), 823–835.

Brandstätter, E., Gigerenzer, G., & Hertwig, R. (2006). The priority heuristic: Making choices without trade-offs. *Psychological Review, 113*(2), 409.

Brighton, H. (2011). *From optimizing to satisficing. Better doctors, better patients, better decisions: Envisioning health care. 2020*, 281.

Brown, D. B., & Sim, M. (2009). Satisficing measures for analysis of risky positions. *Management Science, 55*(1), 71–84.

Camerer, C. F. (1992). Recent tests of generalizations of expected utility theory. *Utility theories: Measurements and applications* (pp. 207–251). Netherlands: Springer.

Caplin, A., Dean, M., & Martin, D. (2011). Search and satisficing. *American Economic Review,* 2899–2922.

Choo, C. W. (1998). *The knowing organization: How organizations use information to construct meaning, create knowledge, and make decisions.* New York: Oxford University Press.

Conlisk, J. (1989). Three variants on the Allais example. *American Economic Review,* 392–407.

Conlisk, J. (1996). Why bounded rationality? *Journal of Economic Literature, 34*(2), 669–700.

Coricelli, G., Diecidue, E., & Zaffuto, F. D. (2016). *Aspiration levels and preference for skewness in choice under risk.* (INSEAD Working Paper No. 2016/28/DSC. SSRN: http://ssrn.com/abstract=2767382).

Day, R. H., & Pingle, M. A. (1991). Economizing economizing. *Behavioral decision making: Handbook of behavioral economics* (pp. 509–522). .

Diecidue, E., & Van De Ven, J. (2008). Aspiration level, probability of success and failure, and expected utility. *International Economic Review, 49*(2), 683–700.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association, 9*(3), 522–550.

Ellsberg, D. (1961). Risk, ambiguity, and the savage axioms. *Quarterly Journal of Economics,* 643–669.

Erev, I., & Barron, G. (2005). On adaptation, maximization, and reinforcement learning among cognitive strategies. *Psychological Review, 112*(4), 912.

Farquhar, P. H. (1984). State of the art—Utility assessment methods. *Management Science, 30*(11), 1283–1300.

Fellner, G., Güth, W., & Maciejovsky, B. (2009). Satisficing in financial decision making—A theoretical and experimental approach to bounded rationality. *Journal of Mathematical Psychology, 53*(1), 26–33.

Fellner, G., Güth, W., & Martin, E. (2006). *Satisficing or optimizing? – An experimental study* (Discussion Paper on Strategic Interaction #11-2006)Jena: Max Planck Institute of Economics.
Gigerenzer, G., & Selten, R. (2001). *Rethinking rationality. Bounded rationality: The adaptive toolbox. 1*, 12.
Gigerenzer, G., Todd, P. M., & The ABC Research Group (1999). *Simple heuristics that make us smart.* Oxford University Press.
Güth, W. (2007). Satisficing in portfolio selection—Theoretical aspects and experimental tests. *Journal of Socio-Economics, 36*(4), 505–522.
Güth, W. (2010). Satisficing and (un) bounded rationality—A formal definition and its experimental validity. *Journal of Economic Behavior & Organization, 73*(3), 308–316.
Güth, W., Levati, M. V., & Ploner, M. (2008). Is satisficing absorbable? An experimental study. *Journal of Behavioral Finance, 9*(2), 95–105.
Güth, W., Levati, M. V., & Ploner, M. (2012). Satisficing and prior-free optimality in price competition. *Economic Inquiry, 50*(2), 470–483.
Hartog, J., Ferrer-i-Carbonell, A., & Jonker, N. (2002). Linking measured risk aversion to individual characteristics. *Kyklos, 55*(1), 3–26.
Heckhausen, H. (1991). *Motivation and action* (P. K. Leppmann, Trans.)Berlin: Springer-Verlag.
Hershey, J. C., & Schoemaker, P. J. (1985). Probability versus certainty equivalence methods in utility measurement: Are they equivalent? *Management Science, 31*(10), 1213–1231.
Hogarth, R. M., & Soyer, E. (2015). Providing information for decision making: Contrasting description and simulation. *Journal of Applied Research in Memory and Cognition, 4*(3), 221–228.
Hu, S., Blettner, D., & Bettis, R. (2011). Adaptive aspiration performance: Performance consequences of risk preferences at extremes and alternative reference groups. *Strategic Management Journal, 32*, 1426–1436. http://dx.doi.org/10.1002/smj.
Kaufman, C., Weber, M., & Haisley, E. (2013). Experience sampling, graphical displays, and risk appetite. *Management Science, 59*(2), 323–340.
Lant, T. K. (1992). Aspiration level adaptation: An empirical exploration. *Management Science, 38*(5), 623–644.
Lanzillotti, R. F. (1958). Pricing objectives in large companies. *American Economic Review, 48*(5), 921–940.
Loomes, G., & Sugden, R. (1982). Regret theory: An alternative theory of rational choice under uncertainty. *Economic Journal,* 805–824.
Lopes, L. L. (1987). Between hope and fear: The psychology of risk. *Advances in Experimental Social Psychology, 20*, 255–295.
Lucier, C. (2004). *Herb Kelleher: The thought leader interview.* Booz & Companyhttp://www.strategy-business.com/article/04212?gko=8cb4f (accessed 14 April, 2016).
Malakhov, S. (2014). Sunk costs of consumer search: Economic rationality of satisficing decision. *Theoretical and practical research in economic fields. 5(1 (9)). Theoretical and practical research in economic fields* (pp. 56–). .
Papi, M. (2012). Satisficing choice procedures. *Journal of Economic Behavior & Organization, 84*(1), 451–462.
Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker.* Cambridge University Press.
Payne, J. W., Laughhunn, D. J., & Crum, R. (1980). Translation of gambles and aspiration level effects in risky choice behavior. *Management Science, 26*(10), 1039–1060.
Pennings, J. M., & Smidts, A. (2003). The shape of utility functions and organizational behavior. *Management Science, 49*(9), 1251–1263.
Rabin, M. (2000). Risk aversion and expected-utility theory: A calibration theorem. *Econometrica, 68*(5), 1281–1292.
Riley, W. B., Jr., & Chow, K. V. (1992). Asset allocation and individual risk aversion. *Financial Analysts Journal, 48*(6), 32–37.
Roy, A. D. (1952). Safety first and the holding of assets. *Econometrica,* 431–449.
Salant, Y. (2011). Procedural analysis of choice rules with applications to bounded rationality. *American Economic Review,* 724–748.
Schmidtz, D. (2004). Satisficing as a humanly rational strategy. In M. Byron (Ed.). *Satisficing and maximizing: Moral theorists on practical reason* (pp. 30–58). New York, NY: Cambridge University Press.
Schwartz, B., Ben-Haim, Y., & Dasco, C. (2011). What makes a good decision? Robust satisficing as a normative standard of rational decision making. *Journal for the Theory of Social Behaviour, 41*, 209–227.
Selten, R. (1998). Features of experimentally observed bounded rationality. *European Economic Review, 42*(3–5), 413–436.
Shipley, D. D. (1981). Pricing objectives in British manufacturing industry. *The Journal of Industrial Economics,* 429–443.
Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics, 69*(1), 99–118.
Simon, H. A. (1957). *Models of man: Social and rational.* Wiley and Sons: New York.
Simon, H. A. (1959). Theories of decision-making in economics and behavioral science. *American Economic Review, 49*(3), 253–283.
Simon, H. A. (1972). Theories of bounded rationality. *Decision and organization. 1. Decision and organization* (pp. 161–176).
Simon, H. A. (1978). Rationality as process and as product of thought. *The American Economic Review, 68*(2), 1–16.
Simon, H. A. (1982). *Models of bounded rationality.* Cambridge, MA: MIT Press.
Starmer, C. (2000). Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk. *Journal of Economic Literature,* 332–382.
Todd, P. M., & Gigerenzer, G. (2003). Bounding rationality to the world. *Journal of Economic Psychology, 24*(2), 143–165.
Tversky, A., & Kahneman, D. E. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*, 1124–1131.
Van Witteloostuijn, A. (1988). Maximising and satisficing opposite or equivalent concepts? *Journal of Economic Psychology, 9*(3), 289–313.
Von Neumann, J., & Morgenstern, O. (1944). *Game theory and economic behavior.* Princeton: Princeton University.
Vriend, N. J. (1996). Rational behavior and economic theory. *Journal of Economic Behavior and Organization, 29*(2), 263–285.
Weber, E. U., Blais, A. R., & Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making, 15*(4), 263–290.
Woike, J., Hoffrage, U., & Martignon, L. (2017). Integrating and testing natural frequencies, Naïve Bayes, and fast-and-frugal trees. *Decision* (Advance online publication).
Woike, J., Hoffrage, U., & Petty, J. S. (2015). Picking profitable investments: The success of equal weighting in simulated venture capitalist decision making. *Journal of Business Research, 68*(8), 1705–1716.

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Berg's research focuses on consumer behavior, financial decision making, medical decision making, choices about food and exercise, the economics of creativity, and the measurement of wellbeing. His work emphasizes decision processes that people actually use (in contrast with the prescriptions of standard economic theory) and their potential to perform well by ignoring what textbooks, decision theorists and economists typically define as rationality. Berg's recent study of how entrepreneurs choose locations reveals evidence that high stakes investment decisions often achieve success by intelligently using face-to-face contacts and highly functional rules of thumb that work well in uncertain and unstable investment environments. Berg argues that economics and finance generally rely on inadequate—oftentimes wrong—measures of how people perceive and reason about risk. Risk management—as well as enjoyment and utilization of the unpredictability of our environments—improves substantially when we look outside bell-curve probability distributions and instead actively undertake to envision new possibilities, or black swans, while using this mode of reasoning to conjure new contingencies and thereby adapt or otherwise achieve satisfactory levels of decision performance in the face of uncertainty and surprise. Berg applies his work on the benefits of risk adaptation in his writing on evidence-based, rather than theory-driven, economic analysis of public policy.

Berg was one of 14 invited speakers (including three Nobel Laureates in economics—Daniel Kahneman, Reinhardt Selten, and Robert Aumann—in addition to other economic theorists such as Ariel Rubinstein) at the Rethinking Rationality Conference in 2012. Berg served on the faculty for the Max Planck Institute's Workshops in Bounded Rationality with Nassim Taleb. His work has attracted invitations to apply his work challenging standard economic theory to the strategic challenges facing some of the most visible names in banking (including two central banks), healthcare, transportation, consumer goods, advertising, hedge fund and wealth management industries.

Berg teaches microeconomics, behavioral economics, psychology and business decision making, financial markets, econometrics, and mathematical economics. He has mentored seven Ph.D. students through completion of their doctoral dissertations and five honors students including two undergraduate research award winners. Berg's research on behavioral economics, judgment and decision making, economic demography and urban economics has attracted repeated coverage, with frequent mentions in national print media and *television appearances, including MSNBC, Fox News, Science News, Business Week, Atlantic Monthly, Slate and the Financial Times*. Since 2006, Berg has served as an elected board member of the Society for the Advancement of Behavioral Economics. *Berg serves as Associate Editor for Global Economics and Management Review (GEMRev)* (Elsevier) and sits on the editorial boards of *Review of Behavioral Economics (ROBE)*, *International Journal of Economics and Business Research*, *Global Business Economics Review* and *Journal of Socio-Economics*. *He reviews and conducts program evaluations for the National Science Foundation, the European Science Foundation and leading academic publishers. Berg receives numerous requests each year for speaking engagements and instructor of short courses and seminars at business schools in Europe, North America and Asia.*

Having advised many graduate students in his former role as Director of Graduate Studies for the Economics Program at UT-Dallas and in his new position as Associate Professor at University of Otago, Berg's approach to building productive research teams has achieved broad success at facilitating creativity and a large volume of inter-disciplinary research outputs. He has assembled student cohorts with heterogeneous and complementary talents based on the premise that diverse strengths and intellectual passions promote agile adaptation to the scientific priorities of the future. He has cultivated multiple research networks that see themselves as ensembles: targeting complementarities, promoting adaptive behavior and encouraging individual entrepreneurship. These research networks substantially enhanced visibility among top researchers and educators of the academic units with which Berg works. As Director of Graduate Studies, Berg's approach expanded both the quantity and quality of masters and Ph.D. programs, as measured by GRE scores, the match between incoming students' research interests and the faculty's areas of expertise, and professional placements for graduates.

As jazz bassist and composer, Berg recorded and toured internationally with jazz trumpeter Maynard Ferguson. He performed with a number of jazz greats, including Clark Terry, J.J. Johnson, Tommy Turrentine, Clarence "C" Sharp, Jimmy Lovelace, Carl Fontana, Joe Morello, Jiggs Wigham, Kei Akagi, Bob Shephard, Alan Broadbent, Peter Bernstein, Bill Stewart, Larry Goldings, Steve Kahn, Don Grolnick, Christy Moore, and John Scofield. Berg wrote music for and acted in the feature film *Patisserie Coin de Rue*, which was released nationally in theaters throughout Japan on February 11, 2011.