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Effects of monetary reserves and rate of gain on human risky choice under budget constraints

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Abstract

The energy-budget rule is an optimal foraging model that predicts that choice should be risk averse when net gains plus reserves meet energy requirements (positive energy-budget conditions) and risk prone when net gains plus reserves fall below requirements (negative energy-budget conditions). Studies have shown that the energy-budget rule provides a good description of risky choice in humans when choice is studied under economic conditions (i.e., earnings budgets) that simulate positive and negative energy budgets. In previous human studies, earnings budgets were manipulated by varying earnings requirements, but in most nonhuman studies, energy budgets have been manipulated by varying reserves and/or mean rates of reinforcement. The present study therefore investigated choice in humans between certain and variable monetary outcomes when earnings budgets were manipulated by varying monetary reserves and mean rates of monetary gain. Consistent with the energy-budget rule, choice tended to be risk averse under positive-budget conditions and risk neutral or risk prone under negative-budget conditions. Sequential choices were also well described by a dynamic optimization model, especially when expected earnings for optimal choices were high. These results replicate and extend the results of prior experiments in showing that humans' choices are generally consistent with the predictions of the energy-budget rule when studied under conditions analogous to those used in nonhuman energy-budget studies, and that choice patterns tend to maximize reinforcement.
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1. Introduction

The energy-budget rule is an optimal foraging model designed to predict how both economic context and the biological needs of an organism influence risk-sensitive foraging choices (Stephens and Krebs, 1986). The energy-budget rule was originally formulated to predict risky choice in a small bird or mammal who needed to acquire a sufficient amount of food while foraging to prevent overnight starvation (Caraco et al., 1980; Stephens, 1981). The model assumes that choice should minimize the probability of an energy shortfall (i.e., starvation). According to the model, whether risk-averse or risk-prone choices will minimize the chance of starvation depends on the organism's energy budget. An energy budget is a description of the energetic status of an organism which is determined by the relationship between the organism's current energy reserves, the expected (mean) rate of energy gain, and the organism's energy requirements. Stephens described a forager's daily energy budget as:

$$\begin{aligned} &\mu n - nr + S_n > R \ \text{(positive energy budget)} \\ &\mu n - nr + S_n < R \ \text{(negative energy budget)} \end{aligned} \tag{1}$$

where μ is mean food intake per interval, n is the number of time intervals (i.e., decisions) in the foraging period, r is the energy expenditure during each interval, S_n is energy reserves, and R is the energy requirement. The energy budget is positive when the mean rate of gain plus reserves is sufficient to meet the energy requirement and is negative when the mean rate of gain plus reserves is insufficient to meet the energy requirement. Stephens showed that, to minimize the chance of starvation, choice should be risk averse under positive-budget conditions and risk prone under negative-budget conditions. Results of studies with a variety of small birds, small mammals, and insects have supported the predictions of the energy-budget rule (for reviews, see Bateson and Kacelnik, 1998; Kacelnik and Bateson, 1996; Real and Caraco, 1986).

Although energy budgets cannot be directly manipulated in human participants due to ethical concerns, several studies have

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investigated whether risky choice in humans is also consistent with the predictions of the energy-budget rule by analyzing choice under conditions analogous to those used in nonhuman energy-budget experiments, such as by using hypothetical budget conditions (e.g., Bickel et al., 2004; Wang, 2002), or by using monetary "earnings budgets" (Pietras and Hackenberg, 2001; Pietras et al., 2003, 2006; Rode et al., 1999). These studies showed that choice patterns were generally in accord with the predictions of the model. For example, Pietras and Hackenberg (2001) simulated energy budgets with monetary earnings budgets by using money gains and earnings requirements instead of food gains and energy requirements. Participants chose between options delivering fixed and variable numbers of points in 5-trial blocks designed to simulate daily foraging periods. To simulate survival contingencies, block earnings were paid to participants only if the earnings exceeded the earnings requirement. Positive and negative earnings budgets were generated by manipulating the value of the earnings requirement. Choice was well described by the energy-budget rule and was risk averse under positive earnings-budget conditions and risk prone under negative earnings-budget conditions.

The psychological processes responsible for the shifts in risk sensitivity across positive and negative energy-budget conditions and positive and negative earnings-budget conditions are not well understood and it is possible that different processes underlie nonhuman and human risky choice. That humans' choice patterns in prior earnings-budget studies were consistent with the energy-budget model suggests, however, that the energy-budget rule may be a useful tool for developing novel predictions about how changes in contextual variables, including resource reserves, expected rates of gain, costs, and resource requirements, affect human risky choice.

In energy-budget studies with nonhumans, the most common method of investigating the effects of energy budget on choice has been to manipulate energy reserves (food deprivation) and/or the mean rate of food delivery (see Kacelnik and Bateson, 1996, but for an example of a study manipulating of requirements see Caraco et al., 1990). For example, in one of the first investigations of the effects of energy budget on choice Caraco et al. (1980) presented birds (yellow-eyed juncos) with choices between options delivering a constant and variable number of seeds. Daily energy requirements were assessed by measuring metabolic rates and rates of daily food intake. During positive energy-budget conditions, subjects were deprived of food for 1 h and seeds were delivered during sessions at a rate that exceeded daily requirements. During negative energy-budget conditions, subjects were deprived for 4 h and seeds were delivered at a rate that fell below daily requirements. Caraco et al. found that choice was risk averse during positive-budget conditions and risk prone during negative-budget conditions.

In contrast to nonhuman energy-budget studies, most studies with humans have investigated risky choice when budgets were manipulated by varying requirements. Only a few studies have investigated the effects of manipulating reserves (deprivation) and/or mean rate of gain on risky choice (Bickel et al., 2004; Wang, 2002). Bickel et al. (2004) investigated choice in opioid-dependent patients between certain and risky hypothetical heroin amounts under conditions of imagined heroin deprivation and satiation, whereas Wang (2002) investigated choice in college students between certain and risky hypothetical disease treatments under conditions of high and low survival probability. In both studies results were generally consistent with the energy-budget rule, but because choice was analyzed under hypothetical conditions, these studies do not permit strong tests of the model's predictions.

In earnings-budget studies, the relationship between rates of gain, reserves, and requirements is precisely controlled, thereby providing more stringent tests of the energy-budget rule. However, no earnings-budget studies have yet investigated whether humans will show shifts in risky choice across positive and negative budgets when earnings budgets are manipulated by varying reserves or rate of gain. Thus, the primary goal of the present research was to investigate risky choice in humans under positive and negative earnings budgets when the earnings budget was manipulated by changing the rate of reinforcement, the reserve level, or both. These manipulations were designed to provide additional tests of the predictions of the energy-budget rule as applied to human behavior by determining whether human risky choice is sensitive to changes in rate of gain and reserves as well as to changes in requirements.

The energy-budget rule is a static model that assumes exclusive risk aversion or risk proneness throughout a foraging period (Houston and McNamara, 1982; Krebs and Kacelnik, 1991; Stephens and Krebs, 1986). If an organism can switch between options however, then switching may increase its chance of survival (Houston and McNamara, 1982). For example, if a forager whose energy budget is negative happens to acquire several large food items, then it may increase its chance of meeting its daily requirement by switching from a high-variance to a low-variance choice option. When choice can vary as a function of current state and state varies as a function of prior choices, optimal choices may be predicted by dynamic optimization models (Houston and McNamara, 1988; Mangel and Clark, 1988).

In the Pietras and Hackenberg (2001) and Pietras et al. (2003) studies with humans, participants could switch between the fixed and variable choice options, and choices sometimes deviated from the predictions of the energy-budget rule. Trial-by-trial choices were therefore evaluated in relation to the predictions of dynamic optimization models to determine whether the deviations were consistent with a more local optimality analysis. In both studies, trial-by-trial choices were often consistent with the predictions of the dynamic models, indicating that choices at each trial (decision stage) within a block tended to maximize the probability of reinforcement. These results support the view that the energy-budget rule may be a useful predictor of risky choice when a single choice occurs (i.e., when choosing a single course of action) but that dynamic models may be better predictors of risky choice when behavior can repeatedly switch between options (Bateson and Kacelnik, 1998; Houston and McNamara, 1982). Additional research is needed, however, to compare static and dynamic energy-budget models and to evaluate human risky choice under dynamic choice conditions. Thus, a second goal of the present research was to further evaluate human risky choice in relation to the predictions of both static and dynamic risk-sensitive optimization models.

2. Method

2.1. Subjects

All procedures were approved by Western Michigan University's Human Subjects Institutional Review Board (HSIRB). The participants were eight adults (four females and four males) recruited via flyers posted around the university. Flyers requested volunteers between the ages of 18–40 years to participate in decision-making research. Participants were selected from the applicant pool based on schedule availability and lack of previous experience with behavioral research. Volunteers reporting current drug use or use of psychoactive medications were excluded. Participants 28, 32, and 49 were 18-year old women, Participant 31 was a 27-year old man, Participants 33 and 57 were 18-year old men, Participant 46 was a 36-year old man, and Participant 56 was a 19-year old woman. During informed consent, participants were told that they would be eligible for a completion bonus of \$1.00 per session if they completed all scheduled sessions. They were also told that earnings could vary day to day and that at the end of the study, if it was determined that their total earnings fell below a \$6.00 average, they would be paid an additional amount to bring their net earnings to a \$6.00 average. No participant required this extra payment. Across participants, average session earnings were \$4.62 (±\$0.64S.D.), average hourly earnings were approximately \$8.67 (±\$1.20S.D.), and average total earnings (without the completion bonus) were \$365.80 (± \$97.85S.D.). All earnings were in US dollars.

2.2. Apparatus

The experiment took place in a 2.13 m × 3.51 m windowless room containing two identical cubicles measuring 1.7 m wide × 1.3 m deep, with 2.1 m high walls. Each cubicle contained a swivel chair, desk, computer monitor, and 3-button response panel. Each cubicle also contained a white noise generator (Marsona TSC-330) to help mask extraneous noise and a camera for real-time observation. Participants were seated alone in one of the two cubicles and were asked to wear earmuffs during experimental sessions to reduce extraneous noise. All experimental events and data monitoring were controlled by computers located in another room using Microsoft Visual Basic© software.

2.3. Procedure

Each session consisted of 16 blocks of five trials. The first six blocks of a session were forced-choice blocks and the remaining 10 were choice blocks. The background of the computer screen was colored black. At the start of each choice trial, the block money counter (with the font colored red) appeared in the top center of the computer screen and the letter "B" surrounded by a box appeared in the lower center of the computer screen. A single response on the response button labeled "B" extinguished the letter "B" and produced the letters "A" and "C" on the lower right and left sides, respectively, of the computer screen. On the screen, letters were approximately 2 cm tall × 1.5 cm wide and were colored in white font. The purpose of the trial-initiation response on the "B" button was to center the participant's hand between the two options at the start of each trial. The letter "A" was correlated with the variable option and the letter "C" was correlated with the fixed option. Five consecutive responses (fixed-ratio or FR 5) on the "A" or "C" response button caused both letters to disappear and added money to the block counter. Switching between options reset the FR 5 response counter. As a form of response feedback, every response on the buttons labeled "A" and "C" changed the font color of the corresponding letter from white to gray for 25 ms. Choosing the fixed option added a constant amount (\$0.06 or \$0.07) to the block counter whereas choosing the variable option added a variable amount (\$0 or \$0.12, $p = .5$, or \$0 or \$0.14, $p = .5$) to the block counter (see Table 1). When the value of the block counter equaled or exceeded the value of the earnings requirement, the font color changed from red to green and remained green until the end of the block. During money-delivery periods (including when the outcome was \$0), the font size of the block counter increased for 0.5 s and then returned to its normal size for 0.5 s. For trials 1–4, the 1-s money-delivery period was followed by a 10-s inter-trial interval (ITI). The block earnings counter remained visible during the ITI.

Following money delivery on the fifth trial of a block, the text "Your Earnings" appeared on the screen above the block-earnings counter. After 6.5 s, a counter labeled "Your Total Earnings" appeared on the screen below the block-earnings counter. After another 6 s, if the amount of money shown on the block counter equaled or exceeded the earnings requirement, then an arrow between the two counters appeared and the block earnings were added to the total earnings at a rate of \$0.01 per 100 ms. If the block earnings were less than the requirement, no money was added to the total counter and the block counter was reset to zero. Twenty-five seconds from the end of the fifth money delivery, all stimuli were removed from the computer screen and the next block began 30-s later (the 25-s delay was designed to exceed the amount of time needed for the maximum possible block earnings to be added to the total counter).

The six forced-choice blocks were similar to choice blocks except that only the fixed or variable option was available for all 5 trials. The schedule type was randomly determined each block with the restriction that each option (fixed or variable) was presented on three blocks. These no-choice trials were designed to ensure that subjects experienced the outcomes of both choice options prior to the choice phase.

The reserve level (the amount shown on the block counter at the start of each block) and/or the mean rate of earnings was manipulated across conditions. The reserve amount was either \$0.03 or \$0.09. The mean rate of gain per trial was either \$0.06 (the fixed option produced \$0.06 with $p = 1$, the variable option produced \$0.00 or \$0.12 with $p = .5$) or \$0.07 (the fixed option produced \$0.07 with p = 1, the variable option produced \$0.00 or \$0.14 with $p = .5$). The earnings requirement

Table 1
Reserves, mean rate of gain, earnings-budget (positive or negative), probability of meeting the requirement for exclusive choice of the fixed and variable option, and prediction across each of the budget conditions

Condition	Reserves	Mean rate	Budget	Fixed Option	Variable Option	Prediction
POS	$0.09	$0.07	Positive	1	.5	Risk aversion
NEG: Rate	$0.09	$0.06	Negative	0	.5	Risk proneness
NEG: Reserves	$0.03	$0.07	Negative	0	.5	Risk proneness
NEG: Rate + Reserves	$0.03	$0.06	Negative	0	.19	Most risk proneness
POS: Rate + Reserves	$0.10	$0.08	Positive	1	.5	Most risk aversion

was $0.40 across all conditions. In the positive earnings-budget condition (POS), the reserve and mean rate of gain was $0.09 and $0.07, respectively. In the negative earnings-budget conditions reserves and the mean rate of gain were manipulated independently (NEG: Reserves and NEG: Rate, conditions, respectively) or in combination (NEG: Rate + Reserves). In the NEG: Rate + Reserves condition, the negative budget was most extreme. Table 1 shows the reserves, the mean rate of earnings, and the predicted pattern of risk sensitivity in each condition. Four participants were exposed to positive-budget conditions prior to negative-budget conditions, and four were exposed to negative-budget conditions first. In most cases, participants were re-exposed to positive-budget conditions between each exposure to negative-budget conditions. In the Pietras and Hackenberg (2001) and Pietras et al. (2003) studies, two negative earnings-budget conditions were compared and choice was more risk averse under the more extreme (higher requirement) conditions. Because the less extreme conditions were experienced first, however, the greater risk taking under the more extreme conditions was confounded with condition sequence. In the present study, the order of exposure to negative-budget conditions was counterbalanced across subjects. Negative-budget conditions were experienced in a BCD sequence (NEG: Rate, NEG: Reserves, NEG: Rate + Reserves) or in a DCB sequence (NEG: Rate + Reserves, NEG: Reserves, NEG: Rate). Table 2 shows the sequence and number of sessions per condition for each subject. Conditions were replicated in a varied order. Each condition lasted for a minimum of 5 sessions and until the numbers of choices for the fixed option per session across 3 consecutive sessions did not vary from the overall mean by more than 5 choices and showed no trends. Due to experimenter error, reserves were set incorrectly for Participant 32 during the NEG: Reserves condition. Data from that condition have been omitted from all analyses.

Two participants (28 and 32) showed little preference for either option under the positive budget condition (POS) (see below). To determine whether a richer earnings-budget would affect preference, these subjects were exposed to a second positive-budget condition in which the reserves and mean rate of earnings were further increased. In this positive-budget condition (POS: Rate + Reserves), the mean rate of earnings was increased to $0.08, and reserves were increased to $0.10.

The following instructions were posted on the wall of the chamber and were read to each participant prior to the first experimental session:

> You may earn points by pressing the button corresponding to the letter shown on the computer screen. During the session, several counters may appear on the computer screen. The counter labeled "your total earnings" shows the total amount of money you have earned during the session. Please remain seated. When you see the words "Session over" appear on the computer screen, you may return to the waiting area.

Sessions were conducted 3–5 days per week, at approximately the same hour. Subjects typically completed 4 sessions per day and each session lasted approximately 32 min. Participants were given a short (5-min) breaks between sessions. Participants were paid in cash the total amount earned in all sessions following the last daily session. At the end of the study, subjects completed four post-experimental questionnaires: a questionnaire containing sets of hypothetical risky choices, the Eysenck impulsivity questionnaire (Eysenck et al., 1985), a Financial Needs Questionnaire (Heffner et al., 2003), and a questionnaire that asked the participant to describe what they did

Table 2
Sequence and number of sessions per condition (in parentheses) for each participant

Condition	Participant							
	28	31	32	33	46	49	56	57
POS	1 (29), 3 (5), 5 (8), 9 (5)	1 (7), 3 (9), 5 (9), 7 (5), 2 (12)	1 (16), 3 (6), 5 (8), 7 (20)	1 (16), 3 (7), 5 (18), 7 (28)	2 (11), 4 (16), 6 (18)	2 (6), 5 (12), 7 (13)	2 (12), 4 (5), 6 (5), 8 (5)	2 (5), 4 (15), 7 (6), 9 (6)
NEG: Rate	6 (6)		2 (13)	6 (5)	5 (8)	1 (9), 6 (12)	5 (6), 9 (5)	1 (12), 5 (6)
NEG: Reserves	4 (16)	4 (7)	4 (8)[a]	4 (9)	3 (7)	3 (25)	3 (6),	3 (6), 8 (6)
NEG: Rate + Reserves	2 (7), 7 (5)	6 (8), 8 (7)	6 (8)	2 (8)	1 (5), 7 (10)	4 (5)	1 (6), 7 (6), 10 (4)	6 (5), 10 (9)
POS: Rate + Reserves	8 (6)	–	8 (11)	–	–	–	–	–

[a] Reserves were programmed incorrectly.

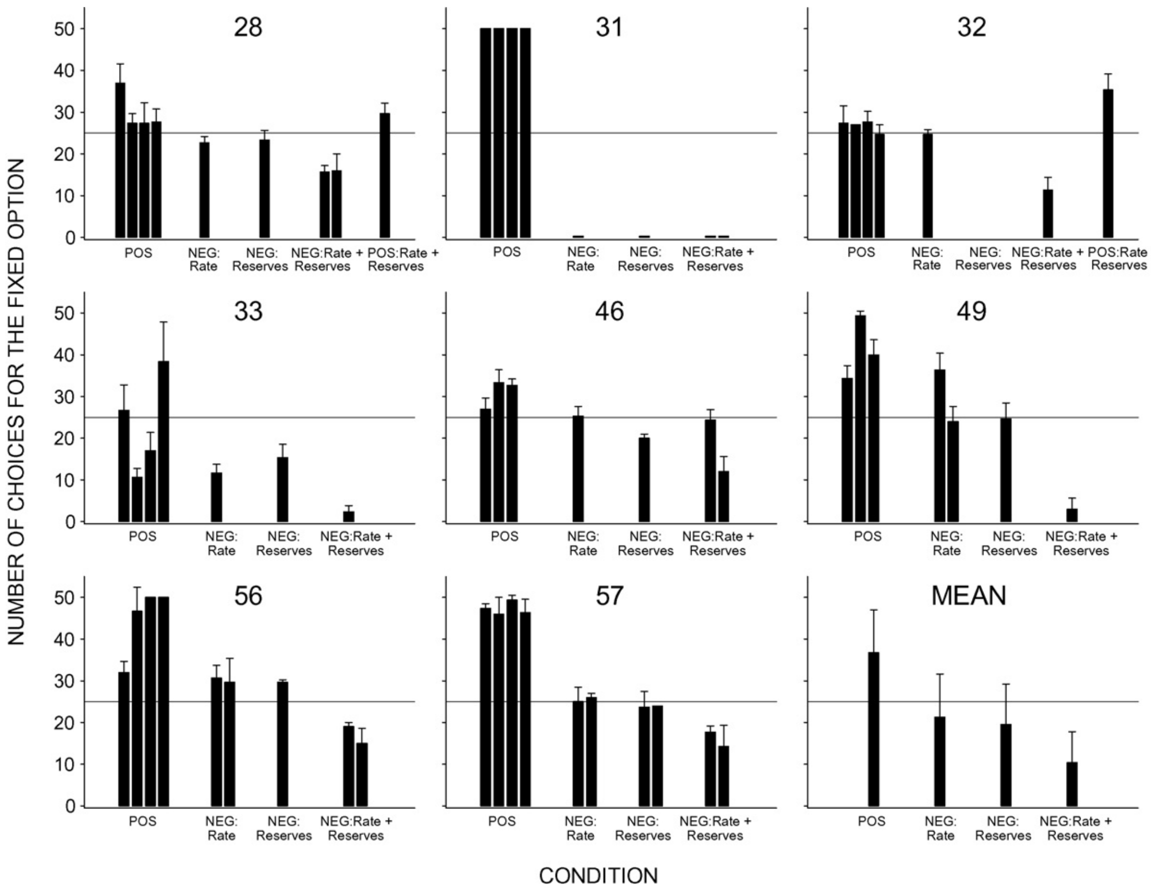

Fig. 1. Mean number choices for the fixed option out of a possible 50 choices across the final 3 sessions of a condition for each participant. Error bars show standard deviations. The horizontal line at 25 indicates the indifference point between the two options. At each condition, bars plotted left to right show results from successive exposures to a condition.

during the experiment. Data from these questionnaires will be reported elsewhere. After participants completed the questionnaires they were paid their completion bonus and were debriefed.

3. Results

3.1. Overall choices

Fig. 1 shows for each participant the mean number of choices for the fixed option (out of 50 possible choices) across the final 3 (stable) sessions of each budget condition. The horizontal line at 25 indicates the midpoint. Thus, bars above the line indicate risk aversion and bars below the line indicate risk proneness. Mean choices were calculated by averaging the mean number of choices for the fixed option across all exposures to a condition for each participant. Under POS conditions, choice tended to be risk neutral (Participants 28, 32, 33) or risk averse (Participants 31, 46, 49, 56 and 57), with mean number of choices for the fixed option equaling 36.7 (73% of choices for the fixed option). Mean number of choices for the fixed option was generally similar under NEG: Rate and NEG: Reserves conditions. Under NEG: Rate and NEG: Reserves conditions choice was typically risk neutral or slightly risk prone, with mean number of choices for the fixed option equaling 21.3 (43%) and 19.5 (39%), respectively. Under NEG: Rate + Reserves conditions, choice was most risk prone, with mean choices for the fixed option equaling 10.4 (21%).

The null hypothesis of no difference among the four condition means (36.7, 21.3, 19.5, and 10.4) was tested using a repeated measures modification (Huitema, 2007a) of the monotonic alternative test proposed by Abelson and Tukey (1963). The predicted ordering of the population means on the number of choices for the fixed option under the four conditions was:

$$\mu_{\mathrm{POS}} > \mu_{\mathrm{NEG:Rate}} = \mu_{\mathrm{NEG:Reserves}} > \mu_{\mathrm{NEG:Rate+Reserves}}$$

A sample contrast (i.e., a weighted sample comparison involving all four means) consistent with the order of the means defined above was tested against the null hypothesis of no difference. The value of the test statistic was $t = 6.37$ (d.f. = 12, $p < .001$); hence it was concluded that a monotonic relationship exists between the order of the mean scores and the pre-specified order of the levels of the independent variable. The size of the relationship between the independent and dependent variables was quite high. Approximately, 69% of the within-subject variation on the outcome measure was explained by the type of experimental condition to which the participants were exposed. This is considered a large effect size.

As described above, choice in two participants (28 and 32) was risk neutral during positive-budget conditions. To examine choice under a richer positive-budget condition, these two

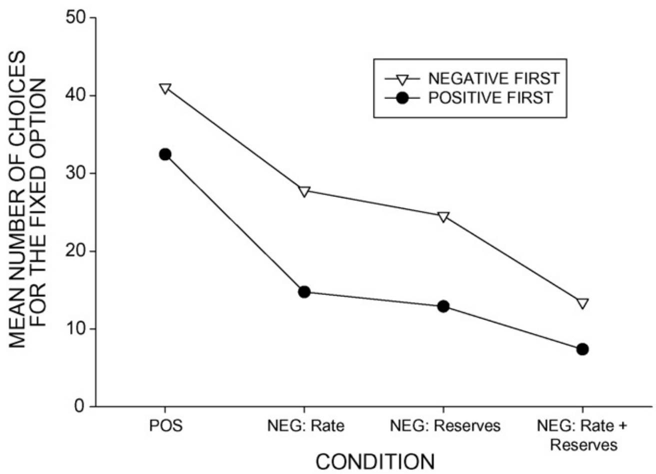

Fig. 2. Mean number of choices for the fixed option across conditions for participants who were exposed to negative budget conditions prior to positive budget conditions (open triangles) and for participants who were exposed to positive budget conditions prior to negative budget conditions (filled circles).

participants were exposed to a condition in which the reserves and mean rate of gain were increased beyond those used in the POS condition. In this extreme positive-budget condition (POS: Rate + Reserves), for Participant 28 risk-averse choices increased only slightly from the last exposure to POS conditions, from approximately 28 to 30 choices, but for Participant 32 risk-averse choices increased more substantially, from approximately 25 to 35 choices.

Fig. 2 shows the mean number of choices for the fixed option across conditions for participants whose first condition of the experiment was a positive-budget condition (28, 31, 32, 33) and a negative-budget condition (46, 49, 56, 59). Choices were first averaged across exposures for each participant, and then averaged across participants. It can be seen in Fig. 2 that for participants exposed to the positive-first sequence and the negative-first sequence, the pattern of choices for the fixed option over the four conditions was similar. This visual impression is consistent with the outcome of the test for interaction (based on the Huynh–Feldt adjusted F analysis) between the type of first exposure factor and the condition factor. The interaction $F = .25$ (d.f. = 2, 12; $p = .78$). It is also apparent in Fig. 2 that the mean number of choices for the fixed option was systematically higher for the subjects exposed to the negative-first sequence than for those exposed to the positive-first sequence. The overall difference between the two sequences as measured by the marginal mean difference $\bar{Y}_{\text{NegFirst}} - \bar{Y}_{\text{PosFirst}} = (26.69 - 17.26) = 9.43$. The test on this difference (using a Welch modified ANOVA F statistic) yielded $F = 9.70$ (d.f. = 1, 6; $p < .03$). The 95% confidence interval on the mean difference is (2.02, 16.84). The sequence factor explains 62% of the observed between-subject variation in choices for the fixed option. The corresponding standardized effect size $d = 2.20$.

As Fig. 3 shows, earnings also varied systematically across budget conditions. Mean earnings during choice trials were \$4.02 under the POS condition, and were \$2.60, \$2.70, and \$1.36, under NEG: Rate, NEG: Reserves, and NEG: Rate + Reserves conditions, respectively. The earnings across conditions indicated that choices tended to maximize the probability of block payment. If choice had been risk prone under positive-budget conditions, mean earnings would have been approximately \$2.86, and if choice had been risk averse under negative-budget conditions, mean earnings would have been \$0.00.

3.2. Dynamic choices

In all but one participant (Participant 31), choices sometimes deviated from the predictions of the energy-budget rule. Trial-by-trial choices in the seven participants whose choices deviated from predictions were therefore evaluated in relation to the predictions of a dynamic optimization model which specified whether a choice for the fixed or variable option would maximize earnings. Specifically, the model calculated expected earnings for each choice at every trial and accumulated earnings (state) combination and the option with the highest expected earnings was designated as optimal. When neither choice for the fixed nor variable option would produce sufficient earnings to meet the requirement, or when fixed and variable choices produced the same expected earnings, neither choice option was designated as optimal. Optimal choices could be either risk averse or risk prone in positive-budget and negative-budget conditions, depending on the expected rate of gain, requirements, accumulated earnings (state), and trials remaining (for a more detailed description of the construction of the model see Pietras and Hackenberg, 2001). Table 3 shows for each condition the trial and earnings combinations at which a choice was designated as optimal, the choice that was optimal (fixed or variable), and the expected values of optimal and nonoptimal choices.

For each participant (except 31), the number of choices for the fixed and variable option at each trial and state combination during the final 3 sessions of each condition were summed. These were then summed across all exposures to a condition, and the proportion of choices for the fixed and variable option at each trial and state combination was calculated. Fig. 4 shows the mean proportion of choices for each option at each trial and state combination across participants. Asterisks above and below the horizontal line indicate that choices for the fixed and variable option, respectively, were optimal. Bars without an asterisk are trial and state combinations at which neither choice was designated as optimal. Bars to the left of vertical lines indicate choices occurring at trial and state combinations for which neither choice would produce sufficient earnings to meet requirements. The energy-budget rule predicts that the proportion of choices for the fixed option should be consistent across trials and levels of accumulated earnings (and should be 1.0 under positive budget conditions and 0 under negative budget conditions), whereas the dynamic model predicts that choice should vary as a function of trial number and level of accumulated earnings. Overall, as Fig. 4 shows, choices tended to vary in a manner consistent with the predictions of the dynamic model. Of 5409 choices that occurred at trial and state values at which a choice was designated as optimal, 4354 (80%) were consistent with predictions. For trial and earning combinations at which neither option would produce enough money to meet requirements (bars to the

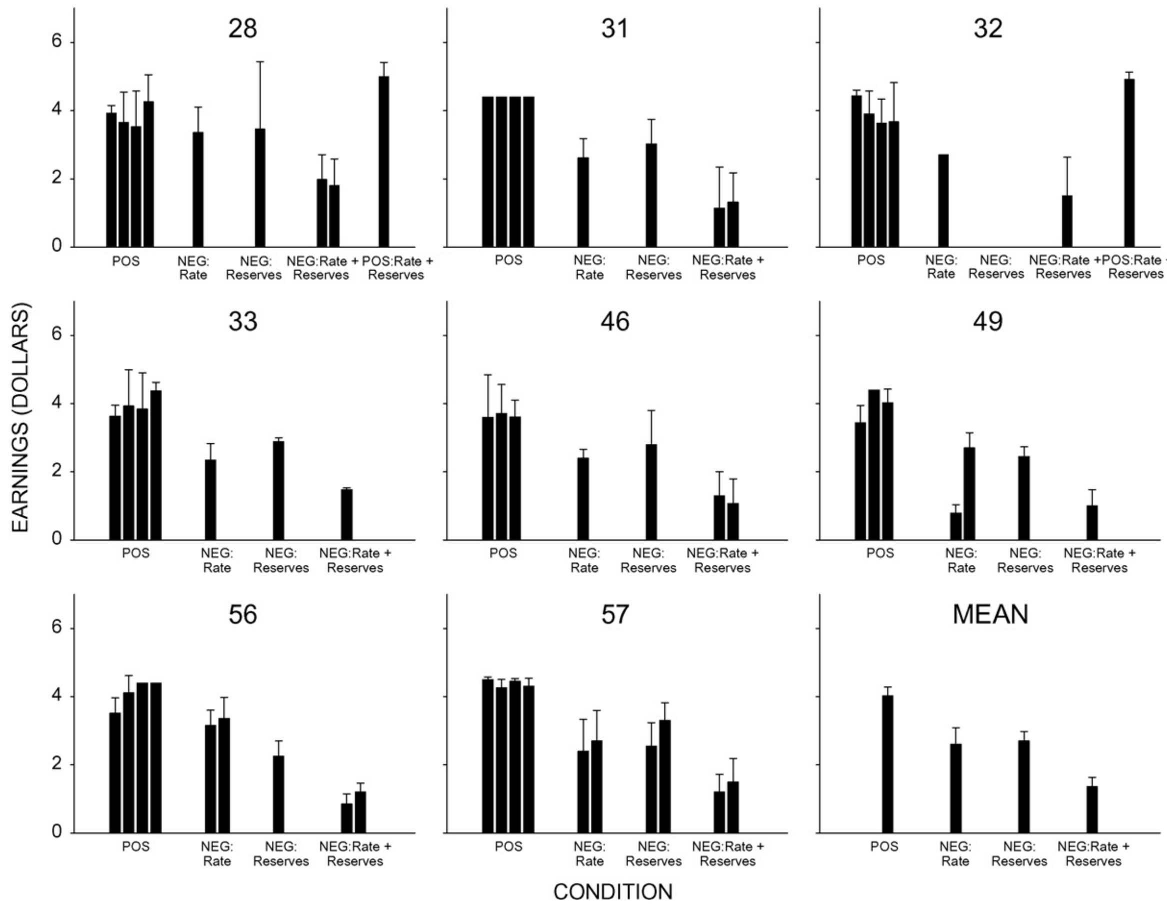

Fig. 3. Mean earnings (in dollars) during choice trials across conditions for each participant. Error bars show standard deviations. At each condition, bars plotted left to right show results from successive exposures to a condition.

left of vertical lines), the variable option was typically preferred. At higher earnings values when neither option was optimal, the fixed option was typically preferred.

The pattern of trial-by-trial choices shown in Fig. 4 is representative of that shown in most participants. Fig. 5 shows for each participant the mean proportion of choices consistent with predictions (averaged across trial blocks) across conditions. In most cases, the proportion of choices consistent with predictions was between .60 and 1.0. Choices were most inconsistent with predictions in the NEG: Rate + Reserves condition, especially for Participants 33 and 49. For Participants 33 and 49, it is likely that the proportions of optimal choices were low during this condition because few choices occurred in trial and state combinations at which a choice was designated as optimal. Also, because choice in these two participants was very risk prone under NEG: Rate + Reserves conditions, few risk-averse choices occurred when risk-aversion was optimal.

Table 4 shows the mean proportion of choices that were consistent with predictions for the fixed and variable option separately. It can be seen in Panel A of Table 4 that the tests on the differences among condition means are nonsignificant with respect to both the fixed and variable options. Panel B provides tests on the difference between fixed and variable options for each condition. Notice that all p-values are $\geq$.40; hence, there is no convincing evidence of differences between the means associated with the two options. Thus, there were no consistent differences between the proportion of fixed choices that were optimal and the proportion of variable choices that were optimal.

Choices tended to become more consistent with the predictions of the dynamic model across trials within a block. Fig. 6 (upper graph) shows the mean proportion of choices consistent with predictions plotted as a function of trial number. The relationship between the proportion of choices consistent with predictions and trial number was modeled using linear regression. Each analysis was carried out by regressing the mean proportion (Y) on trial number (X). The slope coefficient associated with the regression model captures the average change in mean proportion associated with a one trial increase. (This general modeling strategy has been used successfully in many applications, e.g., Methot and Huitema, 1998, and is both more powerful and more parsimonious than the cumbersome method of comparing every mean with every other mean). A separate regression model was fit to the data collected under each of the four conditions displayed in Fig. 6 (upper graph). The method used to estimate the coefficients depended upon the nature of the errors of the model associated with each condition. Ordinary least squares was used for all regressions that appeared to have independent errors; a computer intensive approach developed for the analysis of regression models with autoregressive errors (described in McKnight et al., 2000) was used in cases

Table 3
Optimal choices, with the expected values (in cents) of optimal and nonoptimal choices in parentheses, costs of nonoptimal choices (in cents), and relative expected value of optimal to nonoptimal choices as predicted by the dynamic optimization model at each trial and amount of accumulated earnings across budget conditions. For trial and earnings combinations at which choices for both the fixed and variable option produced the same expected earnings neither option was designated as optimal

Trial number	Condition							
	POS				NEG: Rate			
	Accumulated earnings	Optimal choice	Cost	Relative expected value	Accumulated earnings	Optimal choice	Cost	Relative expected value
1	9	Fixed (44, 39.3)	4.8	0.53	9	Variable (30.9,28.1)	2.8	0.52
2	9				9	Variable (16.9,11.3)	5.6	.60
2	16	Fixed (44, 39.3)	4.8	0.53	15			
2	23				21	Fixed (45, 39.6)	5.4	0.53
3	9				9	Variable (5.6, 0)	5.6	1.00
3	16	Variable (27.5, 22)	5.5	0.56	15			
3	23	Fixed (44, 36.5)	7.5	0.55	21	Variable (28.1,22.5)	5.6	0.56
3	30				27	Fixed (45, 36.7)	8.3	0.55
3	37				33			
4	9				9			
4	16	Variable (11,0)	11	1.00	15			
4	23				21	Variable (11.3,0)	11.3	1.00
4	30	Fixed (44, 36.5)	7.5	0.55	27			
4	37				33	Fixed (45, 36.7)	8.3	0.55
4	44				39			
4	51				45			
5	9				9			
5	16				15			
5	23				21			
5	30	Variable (22, 0)	22	1.00	27			
5	37	Fixed (44,25.5)	18.5	0.63	33	Variable (22.5, 0)	22.5	1.00
5	44				39	Fixed (45,25.5)	19.5	0.64
5	51				45			
5	58				51			
5	65				57			

Trial number	Condition							
	NEG: Reserves				NEG: Rate + Reserves			
	Accumulated earnings	Optimal choice	Cost	Relative expected value	Accumulated earnings	Optimal choice	Cost	Relative expected value
1	3	Variable (30.9, 28.1)	2.8	0.52	3			
2	3	Variable (16.9, 11.3)	5.6	0.60	3			
2	10				9	Variable (16.9, 11.3)	5.6	0.60
2	17	Fixed (45,40.1)	4.9	0.53	15			
3	3	Variable (5.6, 0)	5.6	1.00	3			
3	10				9	Variable (5.6, 0)	5.6	1.00
3	17	Variable (28.1, 22.5)	5.6	0.56	15			
3	24	Fixed (45, 37.2)	7.8	0.55	21	Variable (28.1, 22.5)	5.6	0.56
3	31				27	Fixed (45, 36.7)	8.3	0.55
4	3				3			
4	10				9			
4	17	Variable (11.3,0)	11.3	1.00	15			
4	24				21	Variable (11.3,0)	11.3	1.00
4	31	Fixed (45, 37.2)	7.8	0.55	27			
4	38				33	Fixed (45, 36.7)	8.3	0.55
4	45				39			
5	3				3			
5	10				9			
5	17				15			
5	24				21			
5	31	Variable (22.5, 0)	22.5	1.00	27			
5	38	Fixed (45, 26)	19	0.63	33	Variable (22.5, 0)	23	1.00
5	45				39	Fixed (45,25.5)	19.5	0.64
5	52				45			
5	59				51			

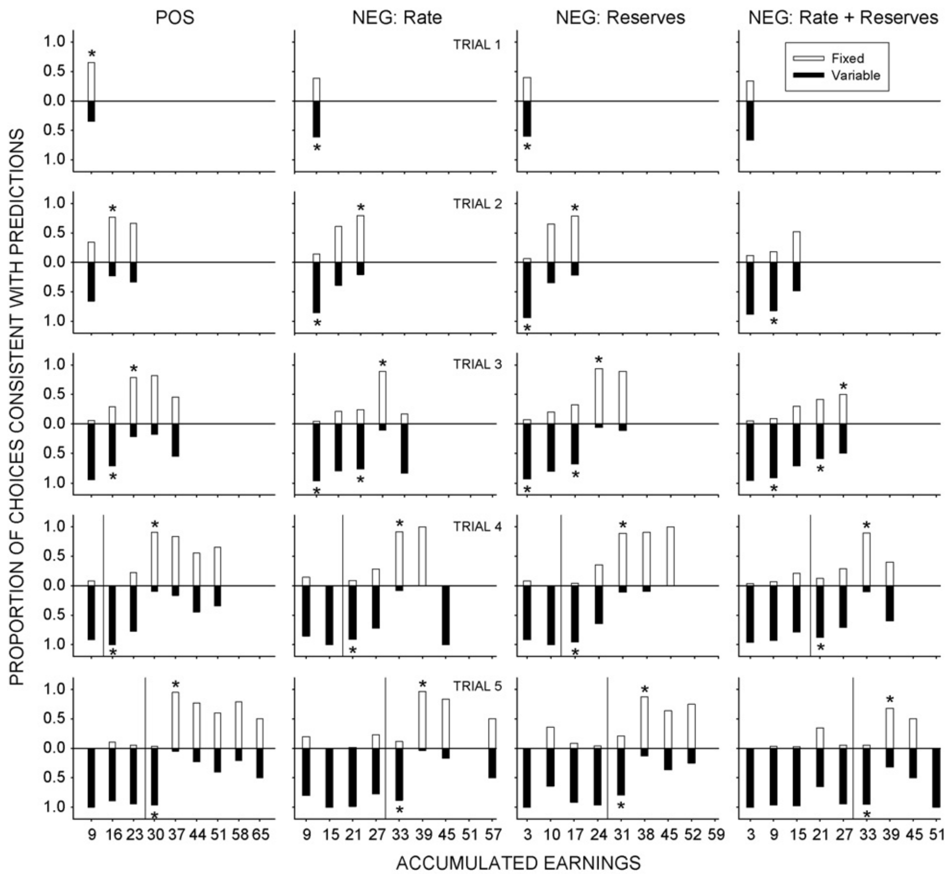

Fig. 4. Mean proportion of choices for the fixed option (open bars above the horizontal axis) and for the variable option (closed bars below the horizontal axis) across trials in each condition plotted as a function of accumulated earnings. Results are the means of stable sessions across participants. Asterisks above the horizontal line indicate that a choice for the fixed option was optimal; asterisks below the horizontal line indicate that a choice for the variable option was optimal. Bars to the left of vertical lines indicate choices that occurred at accumulated earnings value at which neither option could produce sufficient earnings to meet the requirement.

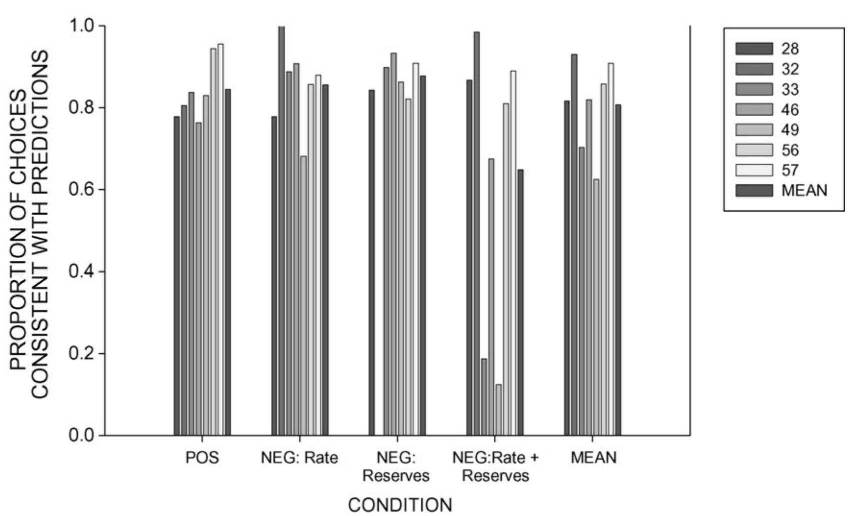

Fig. 5. Proportion of choices consistent with predictions of the dynamic optimization model during the final 3 sessions of a condition for each participant across conditions. Values are the means of all exposures to a condition.

where errors were not independent. Both methods yield an equation that describes the general trajectory of choices across the 5 trials.

There is interest in two types of tests on the slope coefficients. First, it is useful to know if the slope associated with each condition differs significantly from zero. The null hypothesis is $H_0{:}\beta_1 = 0$. Rejection of this hypothesis implies that behavior is a linear function of trials. Second, it is useful to know if there are significant differences between the slopes associated with different conditions (say,

Table 4
Statistical evaluation of mean proportion of choices consistent with predictions of the dynamic model for choices of the fixed and variable option

Panel A[a]

Choice option	Condition means				F	d.f.	p-Value
	POS	NEG: Rate	NEG: Reserves	NEG: Rate + Reserves			
Fixed	.81	.90	.88	.66	2.19	1,7	.18
Variable	.89	.83	.88	.64	3.12	1,8	.11

Panel B[b]

Condition	Mean difference between the fixed and variable options	t	d.f.	p-Value
POS	(.81 − .89) = −.08	−1.11	7	.40
NEG: Rate	(.90 − .83) = .07	.94	7	.46
NEG: Reserves	(.880 − .879) = .001	.02	7	.92
NEG: Rate + Reserves[c]	(.66 − .64) = .02	.60	7	.74

[a] Condition effects for each choice option.
[b] Choice-option effects for each condition.
[c] The near exclusive preference for the variable option in Participants 33 and 49 under the NEG: Rate + Reserves condition resulted in no opportunities for optimal choices for the variable option. Thus, for the statistical analyses values were estimated for these two participants. When data from these two participants are removed, the mean proportions of choices consistent with predictions for the fixed and variable option in the NEG: Rate + Reserves condition are .87 and .83, respectively.

i and j). The null hypothesis associated with comparisons between slopes is $H_0{:}\beta_{1i} = \beta_{1j}$. Rejection of the latter hypothesis implies that the population rate of change in behavior over the 5 trials differs across the conditions being compared.

The results of these two types of test are summarized in Panels A and B in Table 5. In Panel A it can be seen that the first three slope coefficients appear to be similar (all somewhat greater than .07) and that each one strongly contradicts the null hypothesis (all $p \leq .003$). The proportion of the variability on the proportion of choices explained by the linear function of trials (i.e., r^2) is $\geq .25$ for each of the first three conditions. The last slope coefficient is very close to zero and is consistent with the null hypothesis ($p = .94$).

Panel B of Table 5 provides results of tests on the differences between the slopes. Because the data have an unusual dependency structure, conventional procedures for comparing independent slopes are inappropriate. Potentially, there are several sources of dependency among the observations that need to be acknowledged in the analysis, including within-subject carryover from trial to trial within conditions, as well as carryover from condition to condition. Special tests for comparing correlated slopes (described in Huitema, in preparation) were modified (Huitema, 2007b) to accommodate both types of dependency and were carried out to com-

Table 5
Statistical evaluation of mean proportion of choices consistent with predictions of the dynamic model as a function of trials within a block

Panel A[a]

Condition	r	r^2	F	p-Value	Slope b_1	95% CI for β_1
POS	.54	.29	13.45	.001	.077	(.034, .120)
NEG Rate	.50	.25	10.67	.003	.071	(.027, .115)
NEG: Reserves	.52	.27	12.35	.001	.073	(.031,.115)
NEG: Rate + Reserves	.00	.00	.005	.940	.003	(−.077, .082)

Panel B[b]

Conditions compared	F	p-Value	Slope differences	95%CI for difference $\beta_{1i} - \beta_{1j}$
POS–NEG: Rate	.05	.83	.0078	(−.067, .082)
POS–NEG: Reserves	.02	.89	.0047	(−.063, .073)
POS–NEG: Rate + Reserves	2.24	.15	.0553	(−.021, .131)
NEG: Rate–NEG: Reserves	.24	.62	-.0061	(−.063, .073)
NEG: Rate–NEG: Rate + Reserves	3.81	.06	.0683	(−.004, .140)
NEG: Reserves–NEG: Rate + Reserves	2.96	.10	.0699	(−.014, .153)

[a] Slope analyses describing average rate of change (of proportion of choices consistent with predictions) as a function of trials for each condition.
[b] Tests on the differences between slopes associated with different conditions.

Table 6
Statistical evaluation of mean proportion of choices consistent with predictions of the dynamic model as a function of trials within a block for choices of the fixed and variable options

Panel A[a]

Option	r	r^2	F	p-Value	Slope b_1	95% CI for β_1
Fixed	.42	.18	7.10	.01	.0567	(.013, .100)
Variable	.42	.18	7.27	.01	.0617	(.015, .108)

Panel B[b]

Options compared	F	p-Value	Slope differences	95% CI for β_1
Fixed–variable	.018	.89	−.005	(−.080, .070)

[a] Slope analyses evaluating average rate of change (of proportion of choices consistent with predictions) as a function of trials for choices of the fixed and variable options.
[b] Test on the difference between the slopes.

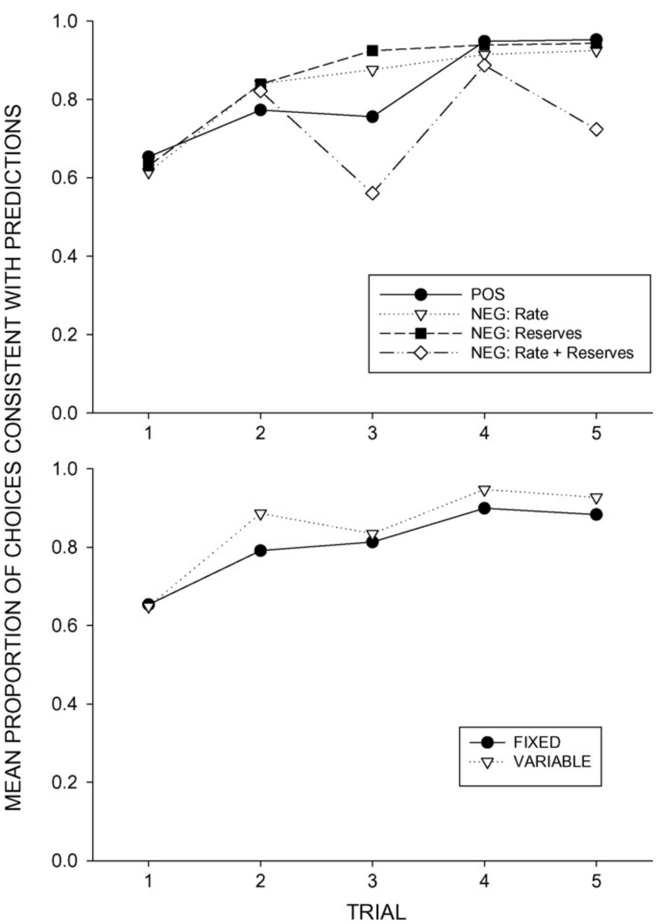

Fig. 6. Mean proportion of choices consistent with predictions of the dynamic optimization model during each condition (upper graph) and for the fixed option and variable option (lower graph) plotted as a function of trial position within a block. Note that neither option was designated as optimal in Trial 1 during NEG: Rate + Reserves conditions (see Table 3).

pare each pair of slopes. It can be seen that the differences among the slopes associated with the first three conditions are clearly not statistically significant (the p-values range from .62 through .83). The tests comparing each condition slope against the slope of the NEG: Rate + Reserves condition yield p-values of .15, .06, and .10; this suggests that the NEG:

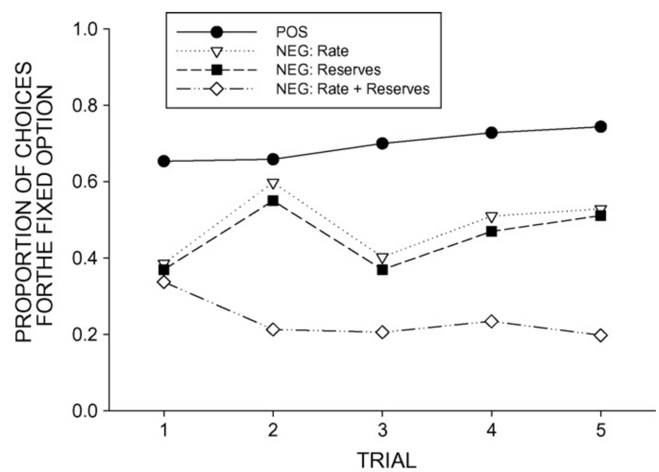

Fig. 7. Mean proportion of choices for the fixed option during the final 3 sessions of each condition plotted as a function of trial position within a block.

Rate + Reserves condition generates a lower slope than do the other conditions.[1]

The lower graph of Fig. 6 shows the proportion of choices consistent with predictions across a block for choices of the fixed option and variable option averaged across conditions. Table 6 lists the results of the slope analyses applied to those data. It can be seen in Panel A that there is a strong association between trials and the mean proportion of choices consistent with predictions (the average proportion of choices consistent with predictions increases about .06 per trial) and in Panel B that there is essentially no evidence of a difference between the slopes associated with the fixed and variable options.

Fig. 7 shows for each condition the mean proportion of choices for the fixed option across trials within a block. There appeared to be no systematic changes in overall proportion of choices for the fixed option across trials. Table 7 shows the results of the slope analyses. It can be seen in Panel A of Table 7

[1] The lack of association between trial number and optimal choices in the NEG: Rate + Reserves condition may be attributed in large part to the choices of Participants 33 and 49 (see above). When the data from these two participants are omitted, the mean proportions of choices consistent with predictions across Trials 2–5 are 0.82, 0.78, 0.89, and 0.89.

Table 7
Statistical evaluation of proportion of choices for the fixed option across trials within a block

Panel A[a]

Condition	r	r^2	F	p-Value	Slope b_1	95% CI for β_1
POS	.17	.03	1.39	.25	.0180	(−.027, .077)
NEG Rate	.13	.02	.54	.47	.0197	(−.035, .074)
NEG: Reserves	.13	.02	.58	.45	.0202	(−.034, .074)
NEG: Rate + Reserves	−.18	.03	1.15	.29	−.0260	(−.075, .023)

Panel B[b]

Conditions compared	F	p-Value	Slope differences	95% CI for difference $\beta_{1i} - \beta_{1j}$
POS–NEG: Rate	.005	.94	−.0014	(−.049, .046)
POS–NEG: Reserves	.004	.95	−.0019	(−.062, .058)
POS–NEG: Rate + Reserves	2.600	.12	.044	(−.012, .100)
NEG: Rate–NEG: Reserves	.000	.99	.0005	(−.004, .003)
NEG: Rate–NEG: Rate + Reserves	2.69	.11	.046	(−.011,.102)
NEG: Reserves–NEG: Rate + Reserves	2.44	.13	.046	(−.014, .106)

[a] Slope analyses describing average rate of change of proportion of choices for the fixed option as a function of trials.
[b] Tests on the differences between slopes associated with different conditions.

that the slope coefficients are similar for all conditions (falling between −.03 and .02) and none contradict the null hypothesis (all $p \geq .25$). Thus, the data are consistent with the hypothesis that there is no average change in the number of fixed choices across trials. Panel B of Table 7 shows that the differences among the slopes associated with each condition are not statistically significant (the p-values range from .11 to .99), indicating no difference in number of fixed choice across trials across the four earnings-budget conditions. These analyses indicate that the increase in optimal choices across trials shown in Fig. 6 could not be accounted for by an overall shift in the number of risk prone or risk-averse choices across trials.

Dynamic optimization models can be used not only to predict optimal choices, but can also be used to predict the costs of nonoptimal choices (Houston and McNamara, 1988). Cost measures are useful in the analysis of optimal choice because optimal responding may be more beneficial at some time and state values than at others (McNamara and Houston, 1986). As shown in Fig. 4, trial-by-trial choices sometimes varied from the predictions of the dynamic model. Therefore, choices were evaluated in relation to costs of nonoptimal choices. Costs were calculated by subtracting expected earnings of nonoptimal choices from expected earnings of optimal choices (see Table 3). Fig. 8 (upper graph) shows for each condition the average proportions of choices consistent with predictions of the dynamic model plotted as a function of cost. The proportion of choices consistent with predictions tended to increase as the cost of nonoptimal choices increased. Although the Pearson correlation between these variables is a reasonably high value ($r = .43$, $p = .009$), it appears that the relationship between these variables is not linear when the original scales are used (note the few cost values in the mid-range). The Pearson correlation increases to .55 ($p = .001$) when the cost variable is transformed to $\log_e$ (cost). Hence, $\log_e$ (cost) explains over 30% of the variation on the mean proportion of choices consistent with predictions.

Cost measures are based on the difference in expected value between optimal and nonoptimal choices. Optimal choices were

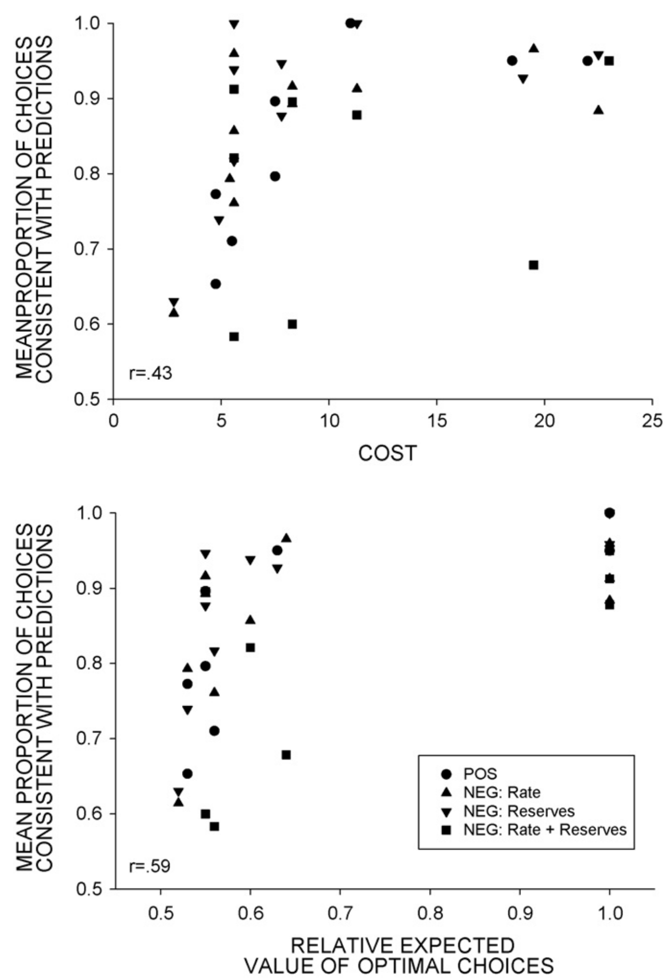

Fig. 8. Mean proportion of choices consistent with predictions of the dynamic optimization model during the final 3 sessions of each condition plotted as a function of the cost of nonoptimal choices (upper graph) and relative expected value of optimal choices (lower graph). See text for details.

therefore also analyzed in relation to the relative expected value of optimal and nonoptimal choices, calculated as the expected value of optimal choices divided by the expected value of optimal plus nonoptimal choices. Relative expected value was similar to cost in that it increased across trials within a block, but differed from cost in that it gave greater value to optimal choices when choosing the nonoptimal alternative would not meet the requirement, i.e., when the relative expected value was 1.0. This occurred whenever choices for the fixed option would not meet the requirement (see Table 3). The scatterplot presented in the lower half of Fig. 8 illustrates the association between relative expected value of optimal choices and mean proportion of choices consistent with predictions. As Fig. 8 (lower graph) shows, in all conditions the mean proportion of choices consistent with predictions of the dynamic model increased as the relative expected value increased, and when the relative expected value was 1.0, the mean proportions of choices consistent with predictions ranged from .88 to 1.0. The linear model is a reasonable descriptor for these data; the Pearson correlation is .59 ($p \leq .001$). On the other hand, a somewhat better description of the data is possible using a quadratic function of the relative expected value variable. In this case the index of correlation (R_I) = .66 ($p < .001$). The improvement of the quadratic model over the linear model is statistically significant ($p = .035$).

4. Discussion

Eight adults were presented with choices between fixed and variable amounts of money across earnings-budget conditions in which mean net gains would (positive earnings budget) or would not (negative earnings budget) meet the earnings requirement. Choices tended to maximize earnings and were typically risk averse in positive earnings-budget conditions and were more risk prone in negative earnings-budget conditions. Choice patterns were therefore consistent with what the energy-budget rule would predict for risk-sensitive foraging choices, and were in accord with the findings of several nonhuman energy-budget studies that have shown shifts in risk sensitivity as a function of budget when budgets were manipulated by altering energy reserves and/or rates of food gain (e.g., Caraco, 1981, 1983; Caraco et al., 1980; Barnard and Brown, 1985). The results also replicate findings of previous studies with humans that have shown that risky choice varies as a function of earnings budget (Pietras and Hackenberg, 2001; Pietras et al., 2003, 2006; Rode et al., 1999). Prior studies with humans have manipulated earnings budgets by varying earning requirements. The present study extends this research by showing that choice also varies as a function of earnings budget when budgets are manipulated by varying reserves and rates of gain.

In the Pietras and Hackenberg (2001) and Pietras et al. (2003) studies investigating choice in humans under positive and negative earnings-budget conditions, two negative earnings-budgets were investigated. In one of the negative-budget conditions the requirement was more difficult to meet and the budget was described as more extreme. In both studies, choice was more risk prone in the more extreme negative-budget condition, but because the more extreme budget condition was always presented after the less extreme condition, budget condition was confounded with condition sequence. In the present study, the order of exposure to a less extreme (NEG: Rate) and a more extreme (NEG: Rate + Reserves) negative earnings-budget condition was counterbalanced across subjects and choice was more risk-prone in the more extreme condition. This finding suggests that in prior studies, the budget condition rather than sequence effects produced the greater risk proneness. In the present study two participants who showed little risk aversion during POS conditions were also exposed to a more extreme positive earnings-budget condition (POS: Rate + Reserves) in which the rate of gain and reserves were increased beyond those in the baseline positive-budget condition (POS). This manipulation increased the number of fixed choices in one of the two participants. Together, these results indicate that risk sensitivity may vary not only as a function of budget, but also as a function of the difference between expected net gains and requirements within a budget condition.

Choice in NEG: Rate and NEG: Reserves conditions was more risk prone than in POS conditions for most participants. In the majority of cases, however, choice in these two negative-budget conditions was indifferent. This contrasts with prior human studies that have shown greater risk proneness in negative earnings-budget conditions (Pietras and Hackenberg, 2001; Pietras et al., 2003). It is likely that choice was less risk prone in NEG: Rate and NEG: Reserves conditions than previously observed because the budget in these two conditions was not as extreme as in prior studies. In the present study the probability of meeting the requirement in these two negative earnings-budget conditions for exclusive risk-prone choices was .5, whereas in the earlier studies it was .19. Moreover, during both the NEG: Rate and NEG: Reserves conditions it was possible to acquire sufficient earnings to switch from the variable to the fixed option after a single choice for the variable option produced high earnings (see Table 3), whereas in prior studies (and in the NEG: Rate + Reserves condition) it was possible to acquire sufficient earnings to switch from the variable to the fixed option only after two or more choices for the variable option produced high earnings. Thus, in previous studies a greater number of risk prone choices was required before switching to the fixed option could meet requirements.

In NEG: Rate and NEG: Reserves conditions, negative budgets were created by manipulating rate of gain or reserves, respectively. In all participants, the number of risky choices was similar in these two conditions, suggesting that both methods of manipulating budgets had comparable effects on choice. This finding is in accord with Eq. (1), which predicts that changes in either reserves or rate of gain can affect budget. Choice was more risk prone in the NEG: Rate + Reserves condition, when both rate of gain and reserves were manipulated together. Choice may have been more risk prone in the NEG: Rate + Reserves condition because both variables were simultaneously manipulated, but it is seems more likely that choice was more risk prone because, as described above, the budget was more extreme.

Interestingly, participants who were exposed to negative earnings-budget conditions prior to positive earnings-budget conditions tended to show greater risk aversion across conditions than those who were exposed to positive earnings-budget conditions first. This suggests that an early experience with poor budget conditions may increase risk aversion. This finding resembles the results of risky-choice research showing that risk aversion sometimes increases after experience with a loss (Thaler and Johnson, 1990). Because there were only four participants exposed to each condition sequence, however, additional studies are needed to evaluate the reliability of this effect.

The energy-budget rule provided an excellent account of choice in Participant 31, but for the remaining seven participants choice was sometimes risk prone during positive-budget conditions and risk averse during negative-budget conditions. These deviations were attributed to the fact that choice could switch between options, and that switching could sometimes increase earnings. Within-block (trial-by-trial) choices were therefore evaluated in relation to the predictions of a dynamic optimization model that predicted optimal responses as a function of accumulated earnings (state) and trial number. As in prior studies (Pietras and Hackenberg, 2001; Pietras et al., 2003), trial-by-trial choices, regardless of whether they were choices for the fixed option or variable option, were frequently consistent with predictions of the dynamic model. This suggests that at each trial and state combination, choices tended to maximize the probability of reinforcement. These findings provide further support for the view that dynamic models may be more useful than static models for predicting risky choice when choice occurs in multiple stages (i.e., sequentially) and when choice can switch between response options (e.g., Houston and McNamara, 1982).

Although choice was typically consistent with the predictions of the dynamic model, choice was more likely to be optimal in later trials of the block than in earlier trials. We speculated that choice may have been more likely to deviate from predictions early in the block because those deviations were less costly. As described above, costs of nonoptimal choices (i.e., the differences in expected value between optimal and nonoptimal choices) varied as a function of trial and state, and were higher later in the block than earlier (see Table 3). When choice was evaluated in relation to costs, as shown in previous studies (Pietras and Hackenberg, 2001; Pietras et al., 2003), choice was more consistent with predictions of the dynamic model when costs were high than when costs were low. Deviations were also evaluated in relation to the relative expected value of optimal choices (i.e., the expected value of optimal choices divided by the expected value of optimal plus nonoptimal choices). Like cost, relative expected value increased across trials, but unlike cost, it predicted that optimal responding would be most likely when nonoptimal choices would not meet requirements. Relative expected value was slightly better correlated with optimal choices than cost, suggesting that it may be a better predictor of optimal responding. In any case, both analyses indicate that choice was sensitive to the reinforcement for both optimal and nonoptimal choices, and support the suggestion of McNamara and Houston (1986) that choice may be inconsistent with the predictions of optimality when the expected values of optimal and nonoptimal choices are similar.

Unlike nonhuman energy-budget studies in which outcomes are typically food deliveries, in the present study the choice outcomes were monetary amounts, and the amounts were relatively small. It is therefore uncertain whether the choice patterns would generalize to humans' choices for larger monetary amounts or more valuable or biologically relevant outcomes. Field studies with humans designed to quantitatively test the predictions of the energy-budget rule could provide important information about the generality of the model's predictions, but unfortunately few such studies have been conducted. Several researchers, however, have investigated humans' choices under conditions that are relevant to the predictions of the energy-budget rule. For example, Miller and Chen (2004) reported that in large companies, risk aversion tended to increase as the difference between current performance and bankruptcy increased. This finding is analogous to the effects of increasing money reserves on risky choice shown in the present study. Similarly, in a review of studies evaluating how business managers perceive risk, March and Shapira (1987) noted that managers reported being more willing to take risks when their organization was doing poorly than when doing well. Studies by anthropologists have also shown that patterns of food sharing among hunter-gatherers (e.g., Kohler and Van West, 1996), patterns of farming in subsistence agriculturalists (e.g., Kunreuther and Wright, 1979), and hypothetical risky choices in pastoralists (e.g., Kuznar, 2001) varied as a function of resource reserves and requirements in a manner qualitatively consistent with the predictions of the energy-budget rule (for a review, see Winterhalder et al., 1999). The consistency of choices across these studies suggests that patterns of risk sensitivity shown in laboratory earnings-budget studies may be relevant to human risky choice across a variety of domains. Additional field studies designed to evaluate risky choice in more naturalistic contexts and laboratory studies designed to evaluate risky choice for more valuable outcomes will be important though, in specifying the range of conditions over which the energy-budget model applies to human choice.

The procedure used in the present study was designed to approximate those used in nonhuman energy-budget studies. Participants were given repeated choices, outcomes were real as opposed to hypothetical, and participants were given experience with the choice outcomes in forced-choice trials prior to the choice phase. Because the choice outcomes were money amounts instead of food amounts, however, the motivational conditions were quite different from those typically arranged in nonhuman experiments. It is possible then, that choice was governed by different behavioral mechanisms (proximate variables) than those governing choice in nonhuman energy-budget studies. In earnings-budget studies with humans, including the present one, results of dynamic optimization analyses suggest that local reinforcement maximization may influence risk preferences. In energy-budget studies with nonhumans, the proximate variables that influence risk preferences are still unclear. Further research is therefore needed to determine whether or not the variables controlling risk sensitivity in humans and nonhumans are actually equivalent.

Regardless of whether or not similar behavioral mechanisms are found to underlie human and nonhuman risky choice, investigating human choice in relation to the predictions of the energy-budget rule will remain an important topic of research. As noted above, the energy-budget rule makes novel predictions about variables that can influence risk sensitivity. Thus, earnings-budget studies can help clarify determinants of human risky choice. Moreover, the similarity in choice patterns across human and nonhuman studies suggests that, despite possible differences in mechanism, the patterns of risk sensitivity generated by the relationship between requirements, mean rates of gain, reserves, and time constraints may have considerable generality. In fact, it is interesting to note that the results of energy-budget and earnings-budget studies are frequently consistent with results of studies by economists and decision researchers that have shown that risky choice in humans may be influenced by the relationship between choice outcomes and the targets, aspirations, requirements, or needs of the decision maker (e.g., Kahneman and Tversky, 1979; Lopes, 1987; March and Shapira, 1987; Payne et al., 1980; Wang, 2002, and see Caraco and Lima, 1987). Thus, studies with humans designed to analyze choice in relation to the predictions of the energy-budget rule may be useful in linking risky-choice research from diverse research traditions.

In summary, the present study showed that risky choice in humans under monetary budget constraints was sensitive to both rate of gain and reserves and that, similar to prior studies with humans (Bickel et al., 2004; Pietras and Hackenberg, 2001; Pietras et al., 2003, 2006; Rode et al., 1999) and nonhumans (e.g., Caraco, 1983; Caraco et al., 1980), choice tended to be more risk prone under poor budget conditions than under richer budget conditions. Such choice patterns tended to maximize the probability of reinforcement. Analysis of within-block choice patterns also indicated that choice at each decision stage tended to maximize expected earnings. Although it remains uncertain whether energy budgets and earnings budgets affect risky choice through similar behavioral mechanisms, that choice patterns were comparable to those shown in a number of prior nonhuman and human studies further suggests that the energy-budget rule may have broad applicability and that it can be a useful model for analyzing human decision making.

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