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Appendix A: Additional Information and Results

A.1. Analysis of the Three Types of Problems in Parts A and B (T_0 and T_p)

We begin with the analysis of T_0. Examining each of the 36 decision problems separately in Parts A and B of T_0 suggests that left-biased choices are more prevalent than right-biased ones in all but two of the problems. Let us order the rules from the most left-biased one to the most right-biased one such that ll is the first and rr is the last. In Part A, the median choice was l (at least 50% of the participants chose ll or l) in all 18 problems. In Part B, the median choice in most problems was s (and l in the rest), suggesting a weaker tendency toward left-biased rules than in Part A.

Even within each part, there are some differences between the problems in the extent of choosing left-biased rules. We now examine how the type of problem (i.e., whether the loss or gain is fixed) affects the tendency to choose left-biased rules. Table S1 presents two indications of this tendency in each of the three types of problems in Parts A and B and compares this tendency to the tendency of choosing right-biased rules. These results establish that left-biased choices are more common in Part A than in Part B, regardless of the type of problem. Further, we find that the tendency toward left-biased choices in the fixed-loss problems is greater than this tendency in the fixed-gain problems in Part A (the average number of left-biased choices is 4.4 vs. 3.67, $t(66) = 2.78$, $p = 0.007$), while the opposite pattern obtains in Part B (2.58 vs. 3.16, $t(66) = -1.95, p = 0.055$).[1]

In Part A, left-biased rules are common in the fixed-loss problems. Intuitively, as the participants cannot control the size of the loss, they focus on the likelihood of the loss. In the fixed-gain problems, participants can control the size of the potential loss and trade off the probability of winning for a smaller potential loss; thus, a smaller proportion of participants choose left-biased rules. Nonetheless, the majority of participants choose left-biased rules in all types of problems in Part A. This finding suggests that when the odds are not on their side, many participants focus on reducing the probability of the potential loss rather than reducing the size of that loss.

[1] All the results in Section A.1 are robust to nonparametric testing.

Table S1. The tendency toward left-biased rules in the three types of questions in Parts A and B of T_0. The third row presents the proportion of participants who tended to choose right-biased rules.

	Part A ($p < 0.5$)			**Part B ($p > 0.5$)**		
	Fixed loss	Fixed gain	Not fixed	Fixed loss	Fixed gain	Not fixed
Range of proportion of participants choosing left-biased rules	66%–79%	55%–64%	55%–69%	34%–51%	48%–54%	42%–49%
Proportion of participants choosing at least 5 (out of 6) left-biased rules	63%	52%	60%	37%	48%	37%
Proportion of participants choosing at least 5 (out of 6) right-biased rules	12%	24%	19%	36%	28%	27%

By contrast, in Part B, where the odds are on the participants' side, it seems that some of the participants' focus shifts toward the potential gain.[2] We suggest that when participants face the fixed-gain problems, they focus on increasing the probability of winning (as they cannot control the size of the gain) by choosing left-biased rules. In the fixed-loss problems, they can also control the size of the potential gain and hence some of them opt for right-biased rules more often.

As for T_p, Table S2 presents two measures of the participants' tendency to choose left-biased rules in each of the three types of problems and compares this tendency to the tendency to choose right-biased rules. The results suggest that left-biased choices are common in T_p as well. Furthermore, we observed a "mirror" pattern similar to that observed in T_0: in Part A the tendency toward left-biased choices in fixed-loss problems is greater than this tendency in fixed-gain problems (the average number of left-biased choices is 4.87 vs. 3.02, $t(46) = 4.8$, $p < 0.001$), whereas in Part B the reverse tendency obtains (1.96 vs. 3.94, $t(46) = -5.09, p < 0.001$).

[2] The participants' explanations provide some indications that, in Part B, they shift attention and focus more on the potential gains than on the potential losses. For example, keywords were classified into the following categories: probability of winning, probability of losing, gain size, and loss size. Accounting for the use of these categories in participants' explanations suggests that the ratio of the probability of winning to the probability of losing increases in Part B (54:29 in Part A and 64:14 in Part B) as does the size of the gain vs. the size of the loss (66:65 in Part A and 54:39 in Part B).

Table S2. Two measures of a tendency toward left-biased rules in the three types of questions in Parts A and B of T_p. The third row presents the proportion of participants who tended to choose right-biased rules.

	Part A ($p < 0.5$)			**Part B ($p > 0.5$)**		
	Fixed loss	Fixed gain	Not fixed	Fixed loss	Fixed gain	Not fixed
Range of proportion of participants choosing left-biased rules	68%–87%	43%–57%	47%–55%	23%–45%	57%–75%	40%–57%
Proportion of participants choosing at least 5 (out of 6) left-biased rules	77%	40%	45%	23%	64%	38%
Proportion of participants choosing at least 5 (out of 6) right-biased rules	2%	26%	23%	47%	15%	15%

The above observations suggest that the patterns of behavior in T_p are similar to those found in T_0. In fact, there are no significant differences between the treatments in the number of left-biased choices in any of the three types of questions.

A.2. Directional Bias in a Simple Context (Part D)

Recall that in Part D, the participants faced 18 decision problems (Q40–Q57). In each problem they chose between two binary *lotteries* with known probabilities of loss and gain. The two lotteries were "mirror images" of each other (i.e., $-x$ with probability p and $+y$ with probability $1-p$ vs. $-y$ with probability $1-p$ and $+x$ with probability p), one negatively skewed and one positively skewed, and had an expected value of roughly 0.

At the aggregate level, 49% of the choices in Part D are of negatively skewed lotteries. In almost all 18 of the problems, the distribution of choices is quite balanced: between 40% and 60% of the choices are of negatively skewed lotteries, where the most extreme frequency of choices of a negatively skewed lottery is 71% (in the first problem in Part D). At the individual level, the number of choices of negatively skewed lotteries (which ranges from 0 to 18) is, on average, 8.75, and its median is 8. Of the 114 participants in the two treatments jointly, we classify 31% of the participants as skewness-averse and 38% as skewness-seeking, if they were consistent in choosing negatively skewed or positively skewed lotteries in 13 or more problems.[3] Despite the slightly different choice pattern, in T_0 the number of choices of negatively skewed lotteries in Part D correlates with the number of left-biased choices in Parts A and B (Pearson's $r = 0.23, p = 0.06$ and Pearson's $r = 0.32, p = 0.009$, respectively). Similarly, the number of choices of positively skewed lotteries in Part D correlates with the number of right-biased choices in Parts A and B (Pearson's $r = 0.23, p = 0.06$ and Pearson's $r = 0.33, p = 0.007$, respectively). In T_p, there is a higher correlation between the behavior in Part D and the behavior in Parts A and B. Nonparametric correlation measures paint a very similar picture.

In conclusion, the participants did not exhibit a preference for negatively skewed lotteries to the extent that could explain the strong general tendency to choose left-biased rules in Parts A and B. Nonetheless, the significant correlation suggests that a preference for negative or positive skewness is related to the tendency to choose left- or right-biased stopping rules. In general, the participants' choices become more balanced when we depart from the context of stopping problems and ambiguous winning probabilities. One possible interpretation of this finding is that the context of a stopping rule and the unknown probabilities encourage the participants to overweight the winning probabilities in instances where the true differences in probabilities (between the five stopping rules) are rather small. This interpretation is also consistent with the results of Part C, namely, with a tendency to estimate the rules' induced lotteries as if the baseline lottery's winning probability were closer to 0.5 than it really is.

Comment: Relation to the literature on skewness-seeking and prudence

The literature on skewness-seeking and prudence documents a preference for positively skewed lotteries. Typically, the proportion of positively skewed choices ranges between 60% and 80%. Thus, the results in the literature are closer to the results in Part D than to the results in Parts A and B. Nonetheless, the proportion of positively skewed choices is still higher in the literature than in Part D. The lower proportion of positively skewed choices may result from the different lotteries that we used (i.e., the two lotteries were mirror images of one another, which possibly emphasized the direction bias) and from order effects (Part D was played after Parts A and B, in which most of the choices were of left-biased rules).

[3] Such consistency occurs with less than 1.5% probability if a participant chooses uniformly at random.

A.3. Alternative Theories

In this section, we present the specifications of the theories mentioned in Section 4.1 that we used in the estimation.

A.3.1 Expected Utility Maximization with Risk Aversion

We examined the two most prominent specifications of this theory: one with constant relative risk aversion (CRRA) and another with constant absolute risk aversion (CARA). Since the classification was virtually unaffected by the choice of whether constant or absolute risk aversion was assumed, we decided to present the CRRA specification, which is perhaps the more prevalent of the two. Recall that, under CRRA, individuals maximize

$$u(x) = \frac{x^{1-\sigma}}{1-\sigma},$$

where x represents final wealth. We assumed that the individuals' initial wealth was 55 because the participants in the experiment were endowed with 55 shekels. We made sure that our classification was robust to different assumptions about individuals' initial wealth.

A.3.2 Cumulative Prospect Theory

The following is Tversky and Kahneman's (1992) unrestricted version of CPT: given a stopping rule $(U, -L; q, 1-q)$, a CPT individual in our setting assigns to the induced *binary* lottery a value of $w^+(q)v(U) + w^-(q)v(-L)$, where $w^+(\cdot)$ and $w^-(\cdot)$ are weighting functions that distort probabilities and $v(\cdot)$ is a value function. Tversky and Kahneman propose the functional forms

$$w^+(q) = \frac{q^\delta}{(q^\delta + (1-q)^\delta)^{\frac{1}{\delta}}} \qquad w^-(q) = \frac{q^\gamma}{(q^\gamma + (1-q)^\gamma)^{\frac{1}{\gamma}}}$$

for the weighting functions and

$$v(x) = \begin{Bmatrix} -\lambda(-x)^\alpha & for\ \ x < 0 \\ x^\beta & for\ \ x \geq 0 \end{Bmatrix}$$

for the value function. Note that since the induced lottery is binary, the decision weights are equal to the probability weighting functions, $w^+(\cdot)$ and $w^-(\cdot)$, and hence there is no need for additional notation for the decision weights.

In the estimation reported in the main text, we used a restricted version in which $\alpha = \beta$ and $\gamma = \delta$. In line with the theory, we imposed that $\alpha \in (0,1]$, $\delta \in (0,1]$, and $\lambda \geq 1$. That is, we assumed that participants are loss-averse, put relatively high (resp., low) weight on low (resp., high) probabilities, and have diminishing sensitivity to gains and losses. In Appendix A.6, we show that the unrestricted version is less successful in explaining our participants' behavior.

A.3.3 Disappointment Aversion

The idea behind disappointment aversion is that individuals may experience disutility when a prospect yields results that are worse than its certainty equivalent. Recall that a stopping rule induces a binary lottery in our setting, where a loss is interpreted as a disappointing outcome and a gain as an elating outcome. Thus, according to Gul's (1991) representation, given an endowment of e and a lottery that induces a loss of l with probability q and a gain of h with probability $1-q$, the disappointment-averse individual obtains a payoff of

$$\left(1+\frac{(1-q)\beta}{1+q\beta}\right)qu(e-l)+\left(1-\frac{q\beta}{1+q\beta}\right)(1-q)u(e+h).$$

In our estimation, we assumed that u is linear and, in line with the literature, that the parameter of disappointment aversion, β, is positive in order to capture disappointment aversion (note that smaller values of β capture elation-loving rather than disappointment aversion). For $\beta=0$, this theory coincides with expected utility theory, and larger values of β capture higher degrees of disappointment aversion.

A.3.4 Salience Theory

Salience theory (Bordalo et al., 2012) assumes that decision makers put more weight on salient states when they evaluate a prospect. Note that each prospect in our experiment (i.e., each stopping rule) has two states, one that corresponds to finishing the game with a gain (we refer to this state as *gain*) and one that corresponds to finishing with a loss (which we refer to as *loss*). We adapt salience theory to our setting by assuming that when individuals evaluate different stopping rules they put more weight on the more salient state. The salience of the different states is determined by the distribution of the stopping rules' potential gains and losses in the decision problem.

Formally, we assume that individuals are characterized by a value function $u(\cdot)$ (which we assume to be linear, following Bordalo et al., 2012), a salience function $\sigma(\cdot)$, and a parameter $\delta \in [0,1]$. The salience of a state is measured by the function $\sigma(\cdot)$, which depends on the difference between the potential gain (resp., loss) induced by the rule and the potential gain (resp., loss) induced by each of the other rules. We denote by η_i the salience ranking of state i according to $\sigma(\cdot)$, where $\eta_i < \eta_j$ implies that state i is more salient than state j, and by π_i the objective probability of state i being realized.

According to salience theory, an individual transforms the objective probabilities π_i and π_j to the subjective probabilities $\hat{\pi}_i$ and $\hat{\pi}_j$ using the following formula:

$$\frac{\pi_i}{\pi_j} = \delta^{\eta_i - \eta_j} \frac{\hat{\pi}_i}{\hat{\pi}_j}.$$

Thus, the lower δ is, the greater the departure from expected utility theory (note that expected utility is a special case of salience theory for $\delta = 1$).

We use h_i and l_i to denote the potential gain and loss induced by rule i. We assume that the salience of the state gain (resp., loss) given rule i depends only on the difference $h_i - \max_{\{j \neq i\}} h_j$ (resp., $l_i - \max_{\{j \neq i\}} l_j$) and that it is increasing in this difference.[4]

It is possible to see that, due to the symmetry of our setting, in decision problems in which the potential loss (resp., potential gain) is fixed across the stopping rules, the state gain (resp., state loss) is more salient than the state loss (resp., state gain), and in problems in which neither the potential loss nor the potential gain is fixed, both states are equally salient. Letting q_i denote the probability of finishing the game with a gain given rule i, we obtain that the expected payoff induced by rule i in Questions 1–6 and 19–24 (fixed potential loss) is

$$v_i = \frac{q_i h_i}{q_i + \delta(1-q_i)} - \frac{\delta(1-q_i) l_i}{q_i + \delta(1-q_i)},$$

and the expected payoff induced by rule i in Questions 7–12 and 25–30 (fixed potential gain) is

$$v_i = \frac{\delta q_i h_i}{\delta q_i + (1-q_i)} - \frac{(1-q_i) l_i}{\delta q_i + (1-q_i)}.$$

Finally, in Questions 13–18 and 31–36 (no fixing), the expected payoff induced by rule i is equal to its induced expected value.

A.3.5 Regret Theory

According to regret theory (Bell, 1982; Loomes and Sugden, 1982), individuals experience regret ex post when a chosen prospect turns out to be inferior to an alternative prospect.

While original regret models are tailored to settings in which individuals choose between two prospects, in our setting, individuals choose one out of five stopping rules. We therefore adapt the theory by assuming that ex post regret is with respect to the *unchosen alternative that turns out to be the best ex post*. Formally, denote by h_i and l_i

[4] We also considered a specification in which the salience of the gain (resp., loss) induced by rule i depends only on the difference $h_i - 0.25 \sum_{\{j \neq i\}} h_j$ (resp., $l_i - 0.25 \sum_{\{j \neq i\}} l_j$). Reverting to this specification does not alter the classification into types.

the potential gains and losses associated with rule i, by e the individual's initial endowment, and by q_i the probability of finishing the game with a gain given rule i. Note that given that the individual chose rule i and finished the game with a gain (or with a loss), the outcome of having chosen rule j instead may be uncertain. For example, suppose that $l_i = l_j = h_i = 15$ and $h_j = 25$. If an individual chose rule i and finished with a gain, she remains uncertain as to whether she would have finished the game with a gain of 25 or a loss of 15 had she chosen rule j instead. Therefore, to adapt regret theory to our setting, we consider the individuals' regret with respect to the maximal *interim expected value* of the other five rules. Formally, let q_{ij}^h (resp., q_{ij}^l) denote the probability of finishing the game with a gain had the individual chosen rule j *conditional on choosing rule i and winning (resp., losing)*. Thus, q_{ij}^h is the probability that the individual would have reached h_j before reaching $-l_j$ given that she reached h_i before reaching $-l_i$. Similarly, q_{ij}^l is the probability that the individual would have reached h_j before reaching $-l_j$ given that she reached $-l_i$ before reaching h_i.

Denote by $u(\cdot)$ the individual's *choiceless utility function*, and let $R(\cdot)$ be a skew-symmetric regret function. The expected value of choosing rule i is

$$\begin{aligned} &q_i u(e+h_i) + (1-q_i)u(e-l_i) + \\ &q_i R(u(e+h_i) - \max_{j\neq i}\{q_{ij}^h u(e+h_j) + (1-q_{ij}^h)u(e-l_j)\}) + \\ &(1-q_i)R(u(e-l_i) - \max_{j\neq i}\{q_{ij}^l u(e+h_j) + (1-q_{ij}^l)u(e-l_j)\}). \end{aligned}$$

Since the literature does not offer one "off-the-shelf" workhorse specification that is suitable for our setting (i.e., for situations in which there are more than two alternatives and there is only partial feedback on unchosen alternatives), we estimated several specifications of preferences that capture regret aversion. As none of these specifications could explain the behavior of a large share of the participants, we report here the specification that could account for the behavior of the largest share of participants. In that specification, $u(\cdot)$ exhibits constant relative risk aversion,

$$R(x) = \begin{cases} g(x) & if\ x \geq 0 \\ -g(-x) & if\ x < 0 \end{cases},$$

and $g(\cdot)$ takes the form of αx^β where $\alpha \geq 0$ captures the intensity of regret and $\beta \geq 1$ ensures that $g(\cdot)$ is convex, which allows us to capture regret aversion. We assumed that the initial wealth is 55 because the participants in the experiment were endowed with 55 shekels. As in Section A.3.1, we made sure that our classification was robust to different assumptions about individuals' initial wealth.

A.4. Participants' Consistency with Decision-Making Theories

Below we report the full results on the consistency of the participants' choices with the choices predicted under the specifications described in A.3. These results are summarized and interpreted in Sections 4.1 and 5.2. Recall that for each individual and each theory, we perform a leave-one-out prediction competition: for each problem, we use a maximum likelihood estimation of the parameters given the choices in the other 35 problems, and predict the individual's choice in that problem given these parameters. The total score of a theory is the number of times in which the prediction was correct. Table S3 presents the results for Treatment T_0 and Table S4 presents the results for Treatment T_p.

Tables S5 and S6 confirm that the conclusions drawn in Sections 4.1 and 5.2 are not sensitive to small modifications in the classification method. Recall that in the classification exercise presented in the paper, we classify a participant into a decision theory if (i) the theory predicts at least 14 of the participant's choices, and (ii) there is no other theory that predicts a higher number of choices. We now modify requirement (ii) and classify a participant into a theory ψ if (i) ψ predicts at least 14 of the participant's choices, and (ii) there is no other theory whose number of correct predictions is greater than the number of ψ's correct predictions by more than $g \in \{0,1,2,3\}$. The number of participants who are classified into each of the theories is weakly increasing in g. However, as shown in Tables S5 and S6, it does not increase by much in our main treatment, T_0. The tables present the classification for $g = 1, 2, 3$ alongside the results for $g = 0$, which are reported in the paper. We conclude that 2S-QTR and CPT remain the only theories that can account for the behavior of a considerable share of the participants in T_0.

Table S3. The leave-one-out score of each theory in Treatment T_0.

Subject	2S-QTR	CRRA	DA	RA	ST	CPT
28	19	5	1	2	11	1
29	18	0	2	3	2	10
33	0	4	6	5	6	7
34	19	1	7	7	7	17
37	27	4	14	14	14	27
39	24	1	4	4	4	11
40	11	0	1	2	1	11
42	36	0	0	0	0	0
43	14	9	9	7	8	13
44	23	5	13	8	8	9

45	36	18	24	25	30	36
46	18	4	6	6	6	18
50	19	11	12	11	16	15
51	13	2	2	3	2	1
57	24	30	29	35	30	35
58	14	3	2	1	2	1
59	27	16	13	9	9	22
60	23	19	21	12	19	27
61	25	12	24	24	18	24
63	0	15	18	15	14	15
64	22	16	16	7	16	24
65	0	1	9	9	9	15
67	16	4	4	4	4	13
68	36	18	24	25	30	36
69	11	0	14	15	14	12
70	28	0	0	2	0	1
71	15	6	7	6	8	5
72	0	2	7	6	7	18
73	24	2	4	4	4	12
74	0	0	0	2	2	1
75	15	0	3	2	3	1
76	32	10	10	10	10	32
81	24	7	13	14	13	24
82	0	1	8	9	8	13
83	21	5	5	5	5	6
85	19	8	8	11	10	9
86	34	0	0	0	0	1
87	0	0	6	5	9	6
88	0	0	1	4	3	2
89	24	16	15	15	24	24
91	12	20	18	12	20	18
94	0	0	4	3	4	4
95	30	8	12	12	12	30
96	30	18	24	25	25	30
97	23	0	1	2	1	7
99	18	12	12	13	17	13
100	13	3	5	6	5	13
102	26	0	1	1	1	5
107	23	17	11	8	8	26
109	23	11	4	4	4	22
110	19	2	7	7	7	19
111	31	3	4	5	7	4
112	28	9	11	11	11	28

115	19	4	10	11	10	19
122	19	0	2	3	2	10
123	13	10	6	10	17	10
124	18	0	2	3	2	10
126	20	3	9	9	9	16
128	21	1	7	7	7	13
131	34	11	11	11	11	34
133	36	18	24	25	30	36
135	36	12	12	12	12	36
136	31	9	11	11	11	31
139	5	3	6	7	9	9
145	11	7	9	10	8	9
146	20	4	5	4	5	6
149	20	3	1	5	4	2

Table S4. The leave-one-out score of each theory in Treatment T_p.

Subject	**2S-QTR**	**CRRA**	**DA**	**RA**	**ST**	**CPT**
26	27	5	5	5	5	5
27	31	12	12	12	12	31
30	21	17	19	11	17	27
31	12	5	5	3	5	4
32	15	11	10	7	12	10
35	22	4	12	12	12	22
36	20	16	15	16	15	19
38	11	7	7	7	7	10
41	12	14	13	14	13	10
47	30	11	12	12	12	30
48	15	20	20	20	20	20
49	36	12	12	12	12	36
52	18	14	14	14	14	19
56	0	15	15	15	15	18
62	17	12	14	7	12	16
66	21	13	13	13	13	21
77	17	11	6	8	12	8
78	17	22	24	15	22	23
80	24	14	14	14	14	19
84	20	23	21	21	20	23
90	27	18	18	18	18	27
92	11	15	15	15	16	13
93	16	18	18	18	18	21
98	6	14	13	14	13	11
101	31	9	12	12	12	31

103	16	20	19	17	18	18
104	36	12	12	12	12	36
106	24	5	11	11	11	24
108	16	19	18	19	18	18
113	14	6	11	14	8	14
114	17	18	20	15	18	19
116	0	16	13	12	17	13
117	25	13	21	17	17	25
118	27	9	10	10	10	27
125	16	9	9	9	9	16
127	0	16	15	15	16	13
132	0	22	23	22	22	23
134	13	4	3	4	3	8
137	25	12	12	12	12	25
138	16	8	8	8	8	16
140	24	12	16	18	18	24
141	26	13	20	19	22	26
142	19	10	5	9	12	8
143	16	21	22	16	21	24
144	0	10	9	10	8	7
147	18	19	18	18	18	22
148	9	15	16	16	16	13

Table S5. The proportion and the number (in parentheses) of participants in T_0 out of the 67 participants that were classified into each of the decision theories.

Theory	*g* = *0*	*g* = 1	*g* = 2	*g* = 3
2S-QTR	69% (46)	69% (46)	70% (47)	72% (48)
Constant Relative Risk Aversion	1.5% (1)	1.5% (1)	1.5% (1)	3% (2)
Disappointment Aversion	1.5% (1)	4.5% (3)	6% (4)	6% (4)
Regret Aversion	3% (2)	4.5% (3)	4.5% (3)	6% (4)
Salience Theory	4.5% (3)	7.5% (5)	7.5% (5)	9% (6)
Cumulative Prospect Theory	33% (22)	36% (24)	39% (26)	40% (27)

Table S6. The proportion and the number (in parentheses) of participants in T_p out of the 47 participants that were classified into each of the decision theories.

Theory	*g* = *0*	*g* = 1	*g* = 2	*g* = 3
2S-QTR	51% (24)	53% (25)	53% (25)	60% (28)
Constant Relative Risk Aversion	15% (7)	23% (11)	28% (13)	36% (17)
Disappointment Aversion	11% (5)	19% (9)	23% (11)	30% (14)
Regret Aversion	13% (6)	19% (9)	21% (10)	28% (13)
Salience Theory	11% (5)	15% (7)	21% (10)	30% (14)
Cumulative Prospect Theory	55% (26)	66% (31)	68% (32)	68% (32)

A.5. Proofs

We now present the proofs of Observations 1 and 2.

Observation 1. *An expected value maximizer would rank the rules as* $ll \succ l \succ s \succ r \succ rr$ *in Questions 1–6 and 25–30, and as* $rr \succ r \succ s \succ l \succ ll$ *in Questions 7–12 and 19–24.*

Proof. The expected value from choosing rule i is $e \times n_i$, where e is the expected value of the baseline lottery and n_i is the expected number of baseline lotteries played given rule i. When $e < 0$ (as in Part A) the expected value of rule i is decreasing in n_i and when $e > 0$ (as in Part B) its expected value is increasing in n_i. Denote by $l_i < 0$ and $h_i > 0$ the potential loss and gain given rule i, respectively. Consider two rules, i and j, such that $l_i = l_j$ and $h_i > h_j$. Observe that $n_i > n_j$ as the two rules induce the same number of lotteries if the process reaches l_j before reaching h_j, and otherwise rule i results in more lotteries. This proves the claim for Questions 1–6 and 19–24. Symmetrically, consider two rules, i and j, such that $h_i = h_j$ and $l_j > l_i$. Here too $n_i > n_j$ as the two rules induce the same number of lotteries if the process reaches h_j before reaching l_j, and otherwise rule i results in more lotteries. This proves the claim for Questions 7–12 and 25–30.■

Observation 2. *Consider an individual whose preferences are represented by equation (2) in the main text and fix a problem from Part A or Part B.*

(i) *There exist parameters* $(\lambda, \alpha, \delta^\star)$ *such that for every* $\delta < \delta^\star$ *an individual who is characterized by* $(\lambda, \alpha, \delta)$ *would rank the rules as* $rr \succ r \succ s \succ l \succ ll$.

(ii) *There exist parameters* $(\lambda, \alpha^\star, \delta)$ *such that for every* $\alpha < \alpha^\star$ *an individual who is characterized by* $(\lambda, \alpha, \delta)$ *would rank the rules as* $ll \succ l \succ s \succ r \succ rr$.

Proof. Consider a problem from our experiment and two rules, $(U_i, -L_i; q_i, 1 - q_i)$ and $(U_j, -L_j; q_j, 1 - q_j)$, such that $U_i \geq U_j$ and $L_j \geq L_i$ with at least one strict inequality. To prove part (i) we need to find a range of parameters for which rule *i* is preferred to rule *j* and to prove part (ii) we need to find a range of parameters for which rule *j* is preferred to rule *i*.

For part (i), fix $\alpha = \lambda = 1$. We start by showing that in the $\delta \to 0$ limit rule i is preferred to rule *j*. Observe that rule *i* is preferred to rule *j* if

$$w(q_i)U_i - w(1 - q_i)L_i > w(q_j)U_j - w(1 - q_j)L_j, \tag{A1}$$

where $w(q) = q^\delta / \left(q^\delta + (1 - q)^\delta\right)^{1/\delta}$. Note that (A1) holds if and only if

$$U_i - \frac{w(1-q_i)}{w(q_i)} L_i > \frac{w(q_j)}{w(q_i)} U_j - w \frac{w(1-q_j)}{w(q_i)} L_j. \quad \text{(A2)}$$

Observe that

$$\lim_{\delta \to 0} \frac{w(1-q_i)}{w(q_i)} = 1 \text{ and } \lim_{\delta \to 0} \frac{w(1-q_j)}{w(q_i)} = \lim_{\delta \to 0} \frac{w(q_j)}{w(q_i)} = \left(\frac{q_i(1-q_i)}{q_j(1-q_j)}\right)^{0.5}.$$

Hence, in the $\delta \to 0$ limit, (A2) becomes

$$U_i - L_i > \left(\frac{q_i(1-q_i)}{q_j(1-q_j)}\right)^{0.5} (U_j - L_j). \quad \text{(A3)}$$

It is easy to see that if $i \in \{rr, r, s\}$ and $j \in \{l, ll\}$, the LHS is nonnegative whereas the RHS is strictly negative. Moreover, since in the symmetric rule $U = L$, the inequality holds for $i = r$ and $j = s$. We now show that inequality (A3) holds for $i = rr$ and $j = r$. To see this, rearrange (A3) and obtain

$$\left(\frac{U_i - L_i}{U_j - L_j}\right)^2 > \frac{q_i(1-q_i)}{q_j(1-q_j)}. \quad \text{(A4)}$$

By design, the LHS of (A4) is equal to 4 in all the problems in our experiment. Moreover, $\frac{q_i}{q_j} < 1$ and $\frac{1-q_i}{1-q_j} < 2$ in all the problems in our experiment. Finally, we show that inequality (A3) holds for $i = l$ and $j = ll$. To see this, rearrange (A3) and obtain (note that the inequality is reversed since $U_j < L_j$):

$$\left(\frac{U_i - L_i}{U_j - L_j}\right)^2 < \frac{q_i(1-q_i)}{q_j(1-q_j)}. \quad \text{(A5)}$$

By design, the LHS of (A5) is equal to 0.25 in all the problems in our experiment. Moreover, $\frac{1-q_i}{1-q_j} > 1$ and $\frac{q_i}{q_j} > 0.5$ in all the problems in our experiment. We conclude that inequality (A3) holds in the $\delta \to 0$ limit. By the continuity of $w(\cdot)$ in δ, there exists a $\delta^\star > 0$ such that (A1) holds for every $\delta < \delta^\star$.

To prove (ii), fix $\delta = 1$ and consider the $\alpha \to 0$ limit, in which the individual assigns to rule i a value of $q_i - \lambda(1-q_i)$. In this limit, the ranking of the rules is $ll \succ l \succ s \succ r \succ rr$ as the value assigned to a rule depends only on the probability q_i. The continuity of the value function in α guarantees (ii).■

A.6. Rank-Dependent Utility and Cumulative Prospect Theory Models

As noted in the main text, recent findings by Ebert and Karehnke (2021) provide an intuition for why CPT can explain the behavior of many our participants. Observation 2 formalizes this intuition in our setting. The same intuition applies for rank-dependent utility models (when coupled with an S-shaped utility function) as these models also accommodate a tendency to overweight low probabilities and underweight high probabilities. We now consider two prominent specifications of such models and establish the analog of Observation 2 for these models. Then, we present a number of prediction competitions in the spirit of the one performed in the main text. In each of these competitions we use a different specification of CPT or rank-dependent utility. Except for this change, the competition is identical to the one presented in the main text.

Consider a specification of rank-dependent utility coupled with an S-shaped utility function like the one suggested in Tversky and Kahneman (1992). An individual with such preferences would assign a value of

$$w(q)U^{\alpha} - (1 - w(q))\lambda L^{\alpha} \tag{A6}$$

to the binary lottery induced by the stopping rule $(U, -L; q, 1-q)$. Goldstein and Einhorn (1987) suggest that

$$w(q) = \frac{bq^{\beta}}{bq^{\beta} + (1-q)^{\beta}} \tag{A7}$$

whereas Prelec (1998) suggests that

$$w(q) = e^{-b(-\ln(q))^{\beta}}. \tag{A8}$$

Under both specifications, $b > 0, \beta > 0, \lambda \geq 1$, and $0 < \alpha \leq 1$.

Observation 3. *Consider an individual whose preferences are represented by (A6), where $w(\cdot)$ is as specified either in (A7) or in (A8), and an arbitrary problem from our experiment.*

(i) There exist parameters $(\alpha, \beta^{\star}, \lambda, b)$ such that for every $\beta < \beta^{\star}$ an individual who is characterized by $(\alpha, \beta, \lambda, b)$ would rank the rules as $rr \succ r \succ s \succ l \succ ll$.

(ii) There exist parameters $(\alpha^{\star}, \beta, \lambda, b)$ such that for every $\alpha < \alpha^{\star}$ an individual who is characterized by $(\alpha, \beta, \lambda, b)$ would rank the rules as $ll \succ l \succ s \succ r \succ rr$.

Proof. Consider two rules, $(U_i, -L_i; q_i, 1-q_i)$ and $(U_j, -L_j; q_j, 1-q_j)$, such that $U_i \geq U_j$ and $L_j \geq L_i$ with at least one strict inequality.

Part (i). Fix α, λ and b. Consider specification (A7) and observe that $\lim_{\beta \to 0} w(q) = b/(b+1)$. Thus, in the $\beta \to 0$ limit, rule *i* is preferred to rule *j* if and only if

$$\left(\frac{b}{b+1}\right) U_i^\alpha - \left(\frac{1}{b+1}\right) \lambda L_i^\alpha > \left(\frac{b}{b+1}\right) U_j^\alpha - \left(\frac{1}{b+1}\right) \lambda L_j^\alpha.$$

The latter inequality holds as $U_i \geq U_j$ and $L_j \geq L_i$ with at least one strict inequality. Consider specification (A8) and observe that $\lim_{\beta \to 0} w(q) = 1/e^b$. Thus, in the $\beta \to 0$ limit, rule *i* is preferred to rule *j* if and only if

$$(1/e^b)U_i^\alpha - (1 - 1/e^b)\lambda L_i^\alpha > (1/e^b)U_j^\alpha - (1 - 1/e^b)\lambda L_j^\alpha.$$

The latter inequality holds as $U_i \geq U_j$ and $L_j \geq L_i$ with at least one strict inequality. To complete the proof of part (i) note that $w(\cdot)$ is continuous in β and the preference for rule *i* over rule *j* implies that $rr \succ r \succ s \succ l \succ ll$.

Part (ii). Fix β, λ and b. In the $\alpha \to 0$ limit, (A6) becomes $w(q) - \big(1 - w(q)\big)\lambda$. Since $q_j > q_i$, it holds that $w(q_j) > w(q_i)$. Hence, in the $\alpha \to 0$ limit, the ranking of the rules is $ll \succ l \succ s \succ r \succ rr$. The continuity of the value function in α guarantees part (ii).■

Next, we perform a series of prediction competitions like the one performed in the main text. For each model, we perform a leave-one-out exercise as described in the main text. We classified a participant into a model if the number of predictions of that model was at least 14 and there was no other model with a larger number of predictions.

We considered five specifications for the CPT/RD model. We used the same S-shaped utility function with loss aversion in all specifications and varied the way probabilities are distorted between them. The first specification corresponds to the specification studied in the main text (equation (2)). The second specification corresponds to Tversky and Kahneman's (1992) unrestricted version of CPT (equation (1)). The third specification corresponds to the RD specification (Goldstein and Einhorn, 1987) in (A6) and (A7). The fourth specification corresponds to the RD specification (Prelec, 1998) in (A6) and (A8). Finally, the fifth specification corresponds to the RD specification in (A6) with the probability distortion function $w(q) = \frac{q^\delta}{\left(q^\delta + (1-q)^\delta\right)^{1/\delta}}$ as suggested by Tversky and Kahneman (1992).

Tables S7 and S8 summarize this exercise and show the results for the CPT/RD specifications as well as for the 2S-QTR model. The results for the remaining specifications we examined (regret aversion, salience theory, disappointment aversion, expected utility with constant relative risk aversion) are not reported for brevity. It should be stressed, however, that regardless of the CPT/RD specification used, these theories explain the behavior of only a few participants in our main treatment.

Table S7. The proportion and the number (in parentheses) of participants in T_0 out of the 67 participants that were classified into each of the models (2S-QTR vs. RD/CPT).

Specification	**RD/CPT**	**2S-QTR**
CPT with $\gamma = \delta$, $\alpha = \beta$ *Tversky and Kahneman (1992); Barberis (2012)*	33% (22)	69% (46)
CPT without restrictions *Tversky and Kahneman (1992)*	13% (9)	67% (45)
RD, Goldstein and Einhorn (1987)	22% (15)	69% (46)
RD, Prelec (1998)	19% (13)	70% (47)
RD, Tversky and Kahneman (1992)	13% (9)	70% (47)

Table S8. The proportion and the number (in parentheses) of participants in T_p out of the 47 participants that were classified into each of the models (2S-QTR vs. RD/CPT).

Specification	**RD/CPT**	**2S-QTR**
CPT with $\gamma = \delta$, $\alpha = \beta$ *Tversky and Kahneman (1992); Barberis (2012)*	55% (26)	51% (24)
CPT without restrictions *Tversky and Kahneman (1992)*	49% (23)	38% (18)
RD, Goldstein and Einhorn (1987)	40% (19)	43% (20)
RD, Prelec (1998)	30% (14)	49% (23)
RD, Tversky and Kahneman (1992)	28% (13)	51% (24)

Appendix B: Experiment's Instructions and Questionnaire*

* Translated from Hebrew

Experiment's Introductory Instructions [were read out loud]

In this experiment, you will play 57 games, one after the other.

As an example, in some of the games you will be asked to choose which lottery out of a number of lotteries you prefer to participate in.

At the end of the experiment, the computer will randomly select for you **one of the 57 games**. For this game only, you will get a payment according to your choice in the game.

For example, if in the selected game you choose to participate in a particular lottery, at the end of the experiment you will actually participate in that lottery and win a monetary prize according to the lottery's outcome.

Thus, you should seriously consider any decision you make: any game out of the 57 games could be the one that determines the amount of money you will receive at the end of the experiment.

Recall that each participant received 55 shekels for participating in the experiment. In the following games, you could win an additional amount or lose part of the initial amount. Nevertheless, it is guaranteed that at the end of the experiment, each participant will be left with at least 25 shekels (out of the 55 shekels).

The experiment consists of 4 parts. At the beginning of each part you will receive instructions for the particular part.

Instructions for Part A

In Part A, you will be presented with a "red or black" gamble (roulette) of the following type:

A participant in the gamble has a probability of 18/37 (0.486) to win 1 shekel and a probability of 19/37 (0.514) to lose 1 shekel.

Each time you participate in the gamble, the computer will implement a lottery (that is, will pick a color for you and will spin a virtual roulette) that determines the outcome, namely, whether you win or lose 1 shekel.

We will let you participate in this gamble over and over again, but will ask you to determine in advance when would you like to stop participating in these gambles.

A "stopping rule" defines the accumulated gain or loss at which you wish to stop participating.

For illustration, if the stopping rule that you chose is

loss	gain
-3	+2

the computer will implement the gamble for you again and again until you accumulate a gain of 2 shekels or until you accumulate a loss of 3 shekels.

Here are a number of possible scenarios:

- If you win the gamble twice in a row, the game will end with a gain of 2 shekels.
- If you lose the gamble 3 times in a row, the game will end with a loss of 3 shekels.
- If you win the gamble once, then lose twice, and then win 3 times, the game will end with a gain of 2 shekels. [This scenario was demonstrated on a graph on the board.]
- If you lose the gamble twice, then win once, and then lose twice, the game will end with a loss of 3 shekels.
- There are additional possible scenarios.

Any questions?

Now enter your ID number on the screen to start the experiment.

Computerized Questionnaire

Part A

Instructions:

In this part, you are given the opportunity to participate over and over again in the following roulette gamble:

- You win 1 shekel with a 18/37 probability (0.486).
- You lose 1 shekel with a 19/37 probability (0.514).

In each of the following 18 games, you are required to choose a "stopping rule," that is, to decide when you wish to stop participating in the gambles (in the case where the game is selected for you for payment in the experiment). You will not be able to change your decision during the course of play.

[Only in T_P: "To ease your choice, the probability of finishing the game with a gain or with a loss will be displayed next to each stopping rule."]

Note that there are no right or wrong answers here; each participant may have different preferences over the gambles.

continue

[The instructions of Part B are almost identical, with the difference that the probabilities of gain and loss in the single roulette gamble are reversed.]

[At the end of Parts A, B, and D, the participants were asked "How would you advise someone else to play for you the games you have just played? Try to explain the principles that guided you in your choices."]

The following is the structure of the questions in Part A and B of T_0:

[In T_P, there was an additional sentence next to each rule: "The probability of finishing the game with a gain is x% and the probability of finishing the game with a loss is (100-x)%."]

Part A [B] – Game x

Choose your preferred stopping rule out of the following 5 rules:

a.

loss	gain
-24	+8

b.

loss	gain
-24	+16

c.

loss	gain
-24	+8

d.

loss	gain
-24	+16

e.

loss	gain
-24	+16

Reminder: The probability of winning a single gamble is 18/37 (0.486) and the probability of losing a single gamble is 19/37 (0.514) in Part B.

continue

Questions 1–18 in Part A

[In all questions in Parts A and B, the 5 available rules appeared in one of two orders (consistently throughout the two parts): from a to e or from e to a.
The probabilities on the right column are for the reader's convenience. They were not given to the participants.]

Part A – Question 1

Rule	Loss	Gain	Probability of gain
a	-21	+9	52%
b	-21	+15	35%
c	-21	+21	24%
d	-21	+27	17%
e	-21	+33	12%

Part A – Question 2

Rule	Loss	Gain	Probability of gain
a	-15	+5	64%
b	-15	+10	44%
c	-15	+15	31%
d	-15	+20	22%
e	-15	+25	16%

Part A – Question 3

Rule	Loss	Gain	Probability of gain
a	-24	+8	57%
b	-24	+16	35%
c	-24	+24	21%
d	-24	+32	14%
e	-24	+40	9%

Part A – Question 4

Rule	Loss	Gain	Probability of gain
a	-27	+9	55%
b	-27	+18	32%
c	-27	+27	19%
d	-27	+36	11%
e	-27	+45	7%

Part A – Question 5

Rule	Loss	Gain	Probability of gain
a	-14	+4	69%
b	-14	+9	46%
c	-14	+14	32%
d	-14	+19	23%
e	-14	+24	17%

Part A – Question 6

Rule	Loss	Gain	Probability of gain
a	-20	+12	42%
b	-20	+16	32%
c	-20	+20	25%
d	-20	+24	20%
e	-20	+28	16%

Part A – Question 7

Rule	Loss	Gain	Probability of gain
a	-25	+17	33%
b	-21	+17	31%
c	-17	+17	29%
d	-13	+17	25%
e	-9	+17	20%

Part A – Question 8

Rule	Loss	Gain	Probability of gain
a	-20	+12	42%
b	-16	+12	39%
c	-12	+12	34%
d	-8	+12	28%
e	-4	+12	18%

Part A – Question 9

Rule	Loss	Gain	Probability of gain
a	-25	+15	37%
b	-20	+15	35%
c	-15	+15	31%
d	-10	+15	25%
e	-5	+15	16%

Part A – Question 10

Rule	Loss	Gain	Probability of gain
a	-28	+20	29%
b	-24	+20	27%
c	-20	+20	25%
d	-16	+20	23%
e	-12	+20	20%

Part A – Question 11

Rule	Loss	Gain	Probability of gain
a	-26	+18	31%
b	-22	+18	30%
c	-18	+18	27%
d	-14	+18	24%
e	-10	+18	20%

Part A – Question 12

Rule	Loss	Gain	Probability of gain
a	-22	+14	38%
b	-18	+14	35%
c	-14	+14	32%
d	-10	+14	27%
e	-6	+14	20%

Part A – Question 13

Rule	Loss	Gain	Probability of gain
a	-25	+5	70%
b	-20	+10	48%
c	-15	+15	31%
d	-10	+20	18%
e	-5	+25	8%

Part A – Question 14

Rule	Loss	Gain	Probability of gain
a	-27	+15	38%
b	-24	+18	31%
c	-21	+21	24%
d	-18	+24	19%
e	-15	+27	14%

Part A – Question 15

Rule	Loss	Gain	Probability of gain
a	-24	+8	57%
b	-20	+12	42%
c	-16	+16	30%
d	-12	+20	20%
e	-8	+24	12%

Part A – Question 16

Rule	Loss	Gain	Probability of gain
a	-26	+10	51%
b	-22	+14	38%
c	-18	+18	27%
d	-14	+22	19%
e	-10	+26	12%

Part A – Question 17

Rule	Loss	Gain	Probability of gain
a	-21	+9	52%
b	-18	+12	41%
c	-15	+15	31%
d	-12	+18	22%
e	-9	+21	15%

Part A – Question 18

Rule	Loss	Gain	Probability of gain
a	-25	+9	54%
b	-21	+13	40%
c	-17	+17	29%
d	-13	+21	19%
e	-9	+25	12%

Questions 1–18 in Part B

Part B – Question 1

Rule	Loss	Gain	Probability of gain
a	-19	+9	82%
b	-19	+14	77%
c	-19	+19	74%
d	-19	+24	71%
e	-19	+29	69%

Part B – Question 2

Rule	Loss	Gain	Probability of gain
a	-14	+6	80%
b	-14	+10	73%
c	-14	+14	68%
d	-14	+18	65%
e	-14	+22	62%

Part B – Question 3

Rule	Loss	Gain	Probability of gain
a	-24	+10	86%
b	-24	+17	82%
c	-24	+24	79%
d	-24	+31	77%
e	-24	+38	75%

Part B – Question 4

Rule	Loss	Gain	Probability of gain
a	-27	+15	86%
b	-27	+21	83%
c	-27	+27	81%
d	-27	+33	80%
e	-27	+39	79%

Part B – Question 5

Rule	Loss	Gain	Probability of gain
a	-20	+8	85%
b	-20	+14	79%
c	-20	+20	75%
d	-20	+26	72%
e	-20	+32	70%

Part B – Question 6

Rule	Loss	Gain	Probability of gain
a	-16	+8	80%
b	-16	+12	74%
c	-16	+16	70%
d	-16	+20	68%
e	-16	+24	65%

Part B – Question 7

Rule	Loss	Gain	Probability of gain
a	-23	+15	82%
b	-19	+15	76%
c	-15	+15	69%
d	-11	+15	59%
e	-7	+15	45%

Part B – Question 8

Rule	Loss	Gain	Probability of gain
a	-27	+21	83%
b	-24	+21	80%
c	-21	+21	76%
d	-18	+21	71%
e	-15	+21	65%

Part B – Question 9

Rule	Loss	Gain	Probability of gain
a	-18	+12	78%
b	-15	+12	72%
c	-12	+12	66%
d	-9	+12	57%
e	-6	+12	45%

Part B – Question 10

Rule	Loss	Gain	Probability of gain
a	-27	+17	85%
b	-22	+17	79%
c	-17	+17	71%
d	-12	+17	60%
e	-7	+17	43%

Part B – Question 11

Rule	Loss	Gain	Probability of gain
a	-28	+22	84%
b	-25	+22	80%
c	-22	+22	77%
d	-19	+22	72%
e	-16	+22	66%

Part B – Question 12

Rule	Loss	Gain	Probability of gain
a	-24	+16	82%
b	-20	+16	77%
c	-16	+16	70%
d	-12	+16	61%
e	-8	+16	48%

Part B – Question 13

Rule	Loss	Gain	Probability of gain
a	-23	+7	89%
b	-19	+11	80%
c	-15	+15	69%
d	-11	+19	56%
e	-7	+23	39%

Part B – Question 14

Rule	Loss	Gain	Probability of gain
a	-27	+11	88%
b	-23	+15	82%
c	-19	+19	74%
d	-15	+23	64%
e	-11	+27	51%

Part B – Question 15

Rule	Loss	Gain	Probability of gain
a	-18	+6	86%
b	-15	+9	76%
c	-12	+12	66%
d	-9	+15	53%
e	-6	+18	38%

Part B – Question 16

Rule	Loss	Gain	Probability of gain
a	-28	+12	88%
b	-24	+16	82%
c	-20	+20	75%
d	-16	+24	65%
e	-12	+28	54%

Part B – Question 17

Rule	Loss	Gain	Probability of gain
a	-20	+8	85%
b	-17	+11	77%
c	-14	+14	68%
d	-11	+17	57%
e	-8	+20	45%

Part B – Question 18

Rule	Loss	Gain	Probability of gain
a	-23	+11	85%
b	-20	+14	79%
c	-17	+17	71%
d	-14	+20	63%
e	-11	+23	53%

Part C (T_0 & T_P)

Instructions:

In this part, you will be asked 3 questions about the gamble from Part A.

In each question, a different "stopping rule" will be presented. For each stopping rule, you will be asked to estimate the probability of finishing the game with a gain, given that this stopping rule is implemented.

In contrast to Part A, in this part there is one correct answer to each question.

For example, if the gamble you can play again and again is

- With a probability of 49%, you win 1 shekel
- With a probability of 51%, you lose 1 shekel

and the stopping rule is

loss	gain
-1	+1

then the probability that the game will end with a gain (of 1 shekel) is exactly 49%.

The closer your answer is to the correct one, the higher the payment you will get for this question (if the question is selected for your payment). The payment you receive will be 40 shekels minus the size of the error in your estimate (in absolute terms).

If, for instance, you estimate that the probability of finishing the game with a gain in the above example is 65%, then the amount of money you could get for this question is 40-|49-65|=24.

continue

Questions 1–3 in Part C

Part C – Question 1

Assume that as in Part A, a participant in the gamble has a probability of 18/37 (0.486) of winning 1 shekel and a probability of 19/37 (0.514) of losing 1 shekel.

If the stopping rule that the participant chooses and that the computer implements is

loss	gain
-25	+25

then what is the probability that the participant will end the game with a gain of 25?

[the correct answer is about 20.5%]

Part C – Question 2

Assume that as in Part A, a participant in the gamble has a probability of 18/37 (0.486) of winning 1 shekel and a probability of 19/37 (0.514) of losing 1 shekel.

If the stopping rule that the participant chooses and that the computer implements is

loss	gain
-25	+50

then what is the probability that the participant will end the game with a gain of 50?

[the correct answer is about 5%]

Part C – Question 3

Assume that as in Part A, a participant in the gamble has a probability of 18/37 (0.486) of winning 1 shekel and a probability of 19/37 (0.514) of losing 1 shekel.

If the stopping rule that the participant chooses and that the computer implements is

loss	gain
-25	+100

then what is the probability that the participant will end the game with a gain of 100?

[the correct answer is about 0%]

Part D (T_0 & T_P)

Instructions:

In this part, you will play 18 games.

In each game, you will be asked to choose between two lotteries.

For simplicity, a lottery in which there is a probability of 63% of winning 13 shekels and a probability of 37% of losing 26 shekels will be presented in the following manner:

Probability	37%	63%
Amount	-26	+13

As explained before, if a particular game is selected for you for payment, the computer will implement your chosen lottery.

continue

Questions 1–18 in Part D

[In each question below, the two available lotteries appeared in a random order, one above the other.]

Part D – Question 1

Probability	35%	65%
Amount	-22	+12

Probability	65%	35%
Amount	-12	+22

Part D – Question 2

Probability	24%	76%
Amount	-25	+8

Probability	76%	24%
Amount	-8	+25

Part D – Question 3

Probability	32%	68%
Amount	-15	+7

Probability	68%	32%
Amount	-7	+15

Part D – Question 4

Probability	19%	81%
Amount	-22	+5

Probability	81%	19%
Amount	-5	+22

Part D – Question 5

Probability	40%	60%
Amount	-24	+16

Probability	60%	40%
Amount	-16	+24

Part D – Question 6

Probability	37%	63%
Amount	-19	+11

Probability	63%	37%
Amount	-11	+19

Part D – Question 7

Probability	25%	75%
Amount	-24	+8

Probability	75%	25%
Amount	-8	+24

Part D – Question 8

Probability	35%	65%
Amount	-17	+9

Probability	65%	35%
Amount	-9	+17

Part D – Question 9

Probability	17%	83%
Amount	-19	+4

Probability	83%	17%
Amount	-4	+19

Part D – Question 10

Probability	29%	71%
Amount	-20	+8

Probability	71%	29%
Amount	-8	+20

Part D – Question 11

Probability	38%	62%
Amount	-16	+10

Probability	62%	38%
Amount	-10	+16

Part D – Question 12

Probability	22%	78%
Amount	-21	+6

Probability	78%	22%
Amount	-6	+21

Part D – Question 13

Probability	37%	63%
Amount	-25	+15

Probability	63%	37%
Amount	-15	+25

Part D – Question 14

Probability	25%	75%
Amount	-18	+6

Probability	75%	25%
Amount	-6	+18

Part D – Question 15

Probability	20%	80%
Amount	-16	+4

Probability	80%	20%
Amount	-4	+!6

Part D – Question 16

Probability	29%	71%
Amount	-24	+10

Probability	71%	29%
Amount	-10	+24

Part D – Question 17

Probability	37%	63%
Amount	-20	+12

Probability	63%	37%
Amount	-12	+20

Part D – Question 18

Probability	33%	67%
Amount	-16	+8

Probability	67%	33%
Amount	-8	+16