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OPTIMAL AND NONOPTIMAL SATISFICING II: AN EXPERIMENTAL ANALYSIS

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ABSTRACT

In this paper the authors report the results of a series of individual choice experiments designed to test the usefulness of a particular theory of satisficing and of conjunctive choice models. Several authors have argued that modeling complicated choice problems by using a conjunctive approach can provide useful simplifications. In fact optimal behavior with these models can involve implementation of extremely complicated strategies. The experiments reported deal with multidimensional search problems structured so that the conjunctive model is appropriate. Four groups of subjects performed the same tasks with similar results. In general, subjects' behavior conforms well to predictions based on optimization and where there is systematic deviation they are consistent with a specific theory of satisficing.

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I. INTRODUCTION

In a recent working paper, Wilde (1981) presented a new approach to the theory of satisficing, the initial observation being that the existing economics literature on satisficing seldom generates testable hypotheses because the models typically fail to include the relevant information acquisition and processing costs (see, e.g., Futia 1977; Radner 1975a, 1975b; Radner and Rothschild 1975; and Winter 1971). By including information acquisition costs, though, it is possible to characterize "optimal" satisficing strategies using the (constrained) optimization techniques familiar to all economists. Moreover, the equations which characterize the optimal satisficing strategy will then be given by a set of first-order conditions. As in most economic problems, these first-order conditions will have a marginal benefit-marginal cost interpretation.

So far, this all seems straightforward. The problem is that the optimal satisficing strategy can still be very complicated, and the whole point of satisficing rules is that they are presumed to be "easier" to use (operationalize) than optimizing rules. The question is whether there is any systematic way of simplifying the optimal satisficing strategy to make it less computationally complex.

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This is where the marginal benefit-marginal cost interpretation of the first-order conditions becomes useful. It is generally possible to preserve the logic of the marginal benefit-marginal cost interpretation but simplify the calculations involved in solving the first-order conditions by ignoring certain kinds of information or interactions, yielding various "nonoptimal" satisficing strategies.

This approach to satisficing has several advantages over the existing literature. First, many nonoptimal satisficing strategies would not be evident in the absence of the formal model. Second, both the optimal satisficing strategy and the nonoptimal satisficing strategies based on it are amenable to comparative statics analysis. Thus we can test which strategy decisionmakers actually use. This highlights the third advantage; the approach makes it unnecessary to make any a priori judgments about which strategies are "easy" and which are "difficult" from a computational point of view, a problem which plagued some of the early literature on satisficing (e.g., Simon, 1955, 1972).

Wilde (1981) developed and illustrated this approach to satisficing in the context of a specific example. The purpose of this paper is to report the results of a series of laboratory experiments designed to test the theory in the context of the same example. Section II will summarize the model and illustrate the comparative statics properties of the optimal satisficing strategy and the various nonoptimal satisficing strategies based on it. Section III will

Consider first equation (1). Here all attributes have been inspected except the last, so that the first $n - 1$ attributes must all exceed their cutoff levels. If this were an optimizing rule, y_{i_n} would be set to take account of the actual observed values of x_1 through x_{n-1} . But y_{i_n} has to be set ex ante. Hence it is set so that the ex ante expected gain from accepting the item, measured by $V_{i_n}^n$, just equals W , the value of searching again.

For the second to the last attribute, the marginal expected gain from inspecting one more attribute, in this case $V_{i_{n-1}}^{i_{n-1}} - W$, is weighted by the likelihood the item will be acceptable, $1 - p_{i_n}$, and compared to the marginal expected cost of observing the last attribute, in this case c_{i_n} . In general (3) reflects similar benefit-cost calculations for the remaining attributes i_1, \dots, i_{n-2} .

The ordering problem is somewhat easier to characterize. Let $R(i) = c_i/p_i$. Then the optimal ordering is to inspect attributes with the smallest values of $R(i)$ first. This rule verifies the intuition that an attribute should be inspected early if it has low inspection costs or a high probability of failure—there is no point in incurring inspection costs on a number of attributes which are likely to be acceptable only to reject the item late in the game on the basis of an attribute which is cheap to inspect or unlikely to be acceptable.

Wilde (1981) also derives comparative statics for the optimal conjunctive strategy. Table 1 presents these for $n = 3$ when $i_1 = 1$, $i_2 = 2$, and $i_3 = 3$. The minus signs in parenthesis mean the

TABLE 1: Comparative Statics for the Optimal Conjunctive Strategy

	c_1	c_2	c_3
y_1^*	(-)	+	+
y_2^*	(-)	-	+
y_3^*	(-)	(-)	-

c_i = sampling cost on attribute i .

y_i^* = optimal cutoff level on attribute i for a risk-neutral decisionmaker.

TABLE 2: Comparative Statics When Sequentiality Is Ignored

	c_1	c_2	c_3
y_1^*	-	+	+
y_2^*	+	-	+
y_3^*	+	+	-

TABLE 3: Comparative Statics When Sequentiality and Simultaneity Are Ignored

	c_1	c_2	c_3
y_1^*	-	0	0
y_2^*	0	-	0
y_3^*	0	0	-

TABLE 4: Comparative Statics When Dynamic Effects Are Ignored

	c_1	c_2	c_3
y_1^*	0	(+)	(+)
y_2^*	0	(-)	(+)
y_3^*	0	0	(-)

TABLE 5: Comparative Statics When Dynamic Effects and Simultaneity Are Ignored

	c_1	c_2	c_3
y_1^*	0	+	+
y_2^*	0	0	+
y_3^*	0	0	0

c_i = sampling cost on attribute i ;

y_i^* = optimal cutoff level on attribute i for a risk-neutral decisionmaker.

then eliciting their cutoff levels. This section will describe the particulars of this process.

Subjects were recruited from social science and business classes. They were told that this was an economics experiment, that they would be paid cash at the end of the experiment (which should last about an hour), and that the minimum payment would be \$5. Higher payments were possible, but could not be guaranteed. Volunteers were given slips of paper stating the time and room number of the experiment. No other information was supplied to the subjects.

During the course of the experiment random numbers were generated using a bingo cage containing balls numbered 0,1,...,9. The numbers 1 to 100 were generated by two draws with replacement; the first draw being the units digit and the second being the tens. Double zero counted as 100. One subject was chosen by lot, or election if the number of volunteers was small enough, to serve as a monitor who inspected the bingo cage and made and recorded the results of the draws from the bingo cage.

Subjects were given three types of problems, three one-attribute, six two-attribute and eight three-attribute, in that order, for a total of seventeen problems. In each case the payoff function was linear in the attributes with unitary coefficients; i.e., $U(x_1) = x_1$, $U(x_1, x_2) = x_1 + x_2$, and $U(x_1, x_2, x_3) = x_1 + x_2 + x_3$, respectively, for the three types of problems. Subjects were informed at the outset of the experiment that they would be rewarded on the basis of their choices for one of the seventeen problems, to be

TABLE 6: Parameter Values for the Two-Attribute Problems and Optimal Cutoffs for Wealth-Maximizing Strategies

Type 2A: $\sum X_1 = [1,11], \sum X_2 = [1,11]$

#	c_1	c_2	y_1^*	y_2^*
1	.25	.25	7.65	6.53
2	2.00	.25	3.84	3.20
3	.25	2.00	8.46	3.28

Type 2B: $\sum X_1 = [3,8], \sum X_2 = [4,12]$

#	c_1	c_2	y_1^*	y_2^*
1	.10	.10	6.20	9.54
2	1.50	.10	3.17	6.86
3	.10	2.50	6.92	5.11

c_i = sampling cost on attribute i .

y_i^* = optimal cutoff level on attribute i for a risk-neutral decisionmaker.

TABLE 7: Parameter Values for the Three Attribute Problems and Optimal Cutoffs for Wealth-Maximizing Strategies

Type 3A: $\sum X_1 = [0,8], \sum X_2 = [0,8], \sum X_3 = [0,8]$

#	c_1	c_2	c_3	y_1^*	y_2^*	y_3^*
1	.10	.10	.10	5.32	4.42	4.02
2	2.00	.10	.10	1.46	1.19	.97
3	.10	2.00	.10	6.54	1.19	.96
4	.10	.10	2.00	5.77	5.15	.74

Type 3B: $\sum X_1 = [0,5], \sum X_2 = [0,10], \sum X_3 = [0,10]$

#	c_1	c_2	c_3	y_1^*	y_2^*	y_3^*
1	.10	.10	.10	2.49	6.24	5.77
2	.75	.10	.10	.15	4.52	4.18
3	.10	3.50	.10	3.92	.81	.60
4	.10	.10	3.50	3.06	7.30	.18

c_i = sampling cost on attribute i .

y_i^* = optimal cutoff level on attribute i for a risk-neutral decisionmaker.

TABLE 8
SUMMARY RESULTS FOR TWO-ATTRIBUTE EQUAL INTERVALS PROBLEMS

$$\sum x_1 = [1,11] \quad \sum x_2 = [1,11]$$

c_1	c_2	y_1^*	y_2^*	MTSAC		PCC		CSUN		UCLA	
				\bar{y}_1	\bar{y}_2	\bar{y}_1	\bar{y}_2	\bar{y}_1	\bar{y}_2	\bar{y}_1	\bar{y}_2
.10	.10	7.65	6.53	6.49	4.90	6.56	4.67	7.38	5.11	7.28	4.62
2.00	.10	3.84	3.20	4.82	3.87	5.01	5.24	4.46	5.32	4.88	4.35
.10	2.00	8.46	3.28	5.80	3.57	7.31	4.37	7.57	3.09	7.06	3.54

SUMMARY RESULTS FOR TWO-ATTRIBUTE UNEQUAL INTERVALS PROBLEMS

$$\sum x_1 = [3,8] \quad \sum x_2 = [4,12]$$

c_1	c_2	y_1^*	y_2^*	MTSAC		PCC		CSUN		UCLA	
				\bar{y}_1	\bar{y}_2	\bar{y}_1	\bar{y}_2	\bar{y}_1	\bar{y}_2	\bar{y}_1	\bar{y}_2
.10	.10	6.20	9.54	5.58	5.68	5.61	6.72	6.13	7.35	6.24	7.07
1.50	.10	3.17	6.86	4.97	5.70	4.60	5.95	4.62	7.00	4.85	6.47
.10	2.50	6.92	5.11	5.75	5.83	5.51	6.00	6.34	5.56	6.13	5.73

c_i = cost per observation on attribute i .

y_i^* = wealth-maximizing cutoff level for attribute i .

\bar{y}_i = average actual cutoff level for attribute i .

TABLE 10: Observed Comparative Statics Results

$$2A: \sum x_1 = [1,11], \sum x_2 = [1,11]$$

MTSAC			PCC		
	Δc_1	Δc_2		Δc_1	Δc_2
$\Delta \bar{y}_1$	-	(-)	$\Delta \bar{y}_1$	(-)	(+)
$\Delta \bar{y}_2$	-	-	$\Delta \bar{y}_2$	(+)	(-)

CSUN			UCLA		
	Δc_1	Δc_2		Δc_1	Δc_2
$\Delta \bar{y}_1$	-	(+)	$\Delta \bar{y}_1$	-	(+)
$\Delta \bar{y}_2$	(+)	-	$\Delta \bar{y}_2$	(-)	-

$$2B: \sum x_1 = [3,8], \sum x_2 = [4,12]$$

MTSAC			PCC		
	Δc_1	Δc_2		Δc_1	Δc_2
$\Delta \bar{y}_1$	-	(+)	$\Delta \bar{y}_1$	-	(-)
$\Delta \bar{y}_2$	(+)	(+)	$\Delta \bar{y}_2$	(-)	(-)

CSUN			UCLA		
	Δc_1	Δc_2		Δc_1	Δc_2
$\Delta \bar{y}_1$	-	(+)	$\Delta \bar{y}_1$	-	(+)
$\Delta \bar{y}_2$	(-)	-	$\Delta \bar{y}_2$	(-)	-

c_i = sampling cost on attribute i ;

\bar{y}_i = average cutoff level on attribute i .

TABLE 12: Observed Comparative Statics Results

$$\underline{3A}: \sum X_1 = [0,8], \sum X_2 = [0,8], \sum X_3 = [0,8]$$

MTSAC				PCC			
	Δc_1	Δc_2	Δc_3		Δc_1	Δc_2	Δc_3
$\Delta \bar{y}_1$	-	(+)	(+)	$\Delta \bar{y}_1$	-	(-)	(+)
$\Delta \bar{y}_2$	(-)	(-)	(+)	$\Delta \bar{y}_2$	(-)	-	(-)
$\Delta \bar{y}_3$	(+)	(+)	(-)	$\Delta \bar{y}_3$	(-)	(-)	-

CSUN				UCLA			
	Δc_1	Δc_2	Δc_3		Δc_1	Δc_2	Δc_3
$\Delta \bar{y}_1$	-	(+)	(+)	$\Delta \bar{y}_1$	-	(-)	(-)
$\Delta \bar{y}_2$	(-)	-	(-)	$\Delta \bar{y}_2$	(-)	-	(-)
$\Delta \bar{y}_3$	(-)	(-)	-	$\Delta \bar{y}_3$	(-)	(-)	-

$$\underline{3B}: \sum X_1 = [0,5], \sum X_2 = [0,10], \sum X_3 = [0,10]$$

MTSAC				PCC			
	Δc_1	Δc_2	Δc_3		Δc_1	Δc_2	Δc_3
$\Delta \bar{y}_1$	(-)	(+)	(+)	$\Delta \bar{y}_1$	-	(-)	(-)
$\Delta \bar{y}_2$	(+)	-	(-)	$\Delta \bar{y}_2$	(-)	-	(+)
$\Delta \bar{y}_3$	(-)	(-)	-	$\Delta \bar{y}_3$	(-)	-	-

CSUN				UCLA			
	Δc_1	Δc_2	Δc_3		Δc_1	Δc_2	Δc_3
$\Delta \bar{y}_1$	-	(-)	(-)	$\Delta \bar{y}_1$	-	(-)	(+)
$\Delta \bar{y}_2$	(+)	-	(-)	$\Delta \bar{y}_2$	(-)	-	(+)
$\Delta \bar{y}_3$	(+)	(-)	-	$\Delta \bar{y}_3$	(-)	(-)	-

c_i = sampling cost on attribute i ;

\bar{y}_i = average cutoff level on attribute i .

TABLE 14: Ordering of Individual Cutoff Levels
(Equal Intervals and Equal Costs)

Two Attributes					
Group	(1) $y_1 > y_2$	(2) $y_1 = y_2$	(3) $y_1 < y_2$	Probability of at Least as Many $y_1 > y_2$	
				$p = 1/3$	$p = 1/2$
				MTSAC	20
PCC	15	12	3	.0435	.0038
CSUN	17	2	3	.0000	.0013
UCLA	36	5	2	.0000	.0000
Total*	88	25	15		

*Based on the null hypothesis that $p = 1/3$, $t = 8.5$.

Based on the null hypothesis that $p = 1/2$, $t = 7.2$.

TABLE 15: Ordering of Individual Cutoff Levels
(Equal Intervals and Equal Costs)

Three Attributes					
Group	(1)*	(2)**	(3)**	(4)**	(5)***
	$y_1 > y_2 > y_3$	$y_1 > y_2$	$y_1 > y_3$	$y_2 > y_3$	$y_1 > y_2 = y_3$
MTSAC	18	10	9	3	6
PCC	17	6	5	2	4
CSUN	7	8	8	2	6
UCLA	17	11	11	3	6
Total	59	35	33	10	22

*Based on the null hypothesis that $p = 1/13$, $t = 16.3$.

**Counts in addition to those shown in column 1. Based on the null hypothesis that $p = 1/3$, for

$$y_1 > y_2, t = 9.6;$$

$$y_1 > y_3, t = 9.2;$$

$$y_2 > y_3, t = 4.9.$$

***Also counted in columns 2 and 3.

TABLE 16: Individual Choices of Problems for Payment (Theoretical Cutoffs)

Group	2A.2 and 2A.3				3A.2, 3A.3, and 3A.4			
	N	# Right	P*	t	N	# Right	P*	t
MTSAC	27	16	.221	0.96	30	15	.044	1.94
CSUN	22	17	.009	2.56	21	16	.000	4.17
UCLA	42	32	.001	3.39	43	31	.000	5.39
Group	(Wealth-Maximizing Strategy) 3B.2, 3B.3, and 3B.4				(High-Cost Last Strategy) 3B.2, 3B.3, and 3B.4			
	N	# Right	P*	t	N	# Right	P*	t
MTSAC	33	12	.419	0.37	33	10	.565	-0.37
CSUN	22	8	.293	0.30	22	9	.163	0.75
UCLA	43	21	.012	2.16	43	19	.050	1.51

*Probability of at least as many right, assuming choice of problems is to be equally likely.

interested in understanding the extent to which people grasp the nature of the conjunctive choice rule at a more or less intuitive level. During the last decade, there has been a growing belief among consumer researchers that the conjunctive rule is often used as an initial screening device in complex choice situations (see Bettman [1979] for a discussion of this research). If this is true then it is clearly important to understand whether people use the rule "properly" and, if they do not, the nature of their difficulties with it. We shall discuss the implications of our experiments for consumer research elsewhere but an obvious question is whether performance might not improve with familiarity. The likely answer to this question is yes. The more significant questions are by how much and in what ways. If the changes in performance as we move from MTSAC to PCC to CSUN to UCLA are any indication, it appears reasonable to conjecture that improvements due to familiarity are likely to be statistically significant but not qualitatively significant. There is an obvious set of experiments which could test this conjecture, but we have not as yet run them.

The learning issue also is important in the context of the theory of satisficing these experiments are meant to test. A traditional, market-oriented economist would reject all theories of satisficing as irrelevant since learning behavior, conditioned by the discipline of the market, will ultimately make agents act as if they are maximizing. This makes more sense in the theory of the firm than in the theory of consumer behavior, but even there it misses the

point. If agents fail to optimize because of computation costs, then learning or familiarity with a problem should not change the qualitative behavior of agents unless it reduces those costs. What it is likely to do is make agents perform better at whatever nonoptimal level they chose to locate. In other words, it should reduce the variance in their behavior but not change its qualitative nature. This is, in fact, precisely what we saw in these experiments.

Overall, our results are quite striking. First, the behavior of people without prior training corresponds in several ways to predictions based on optimizing behavior. Thus, as the cost of inspecting a dimension increases, people tend to search less on that dimension. For two- and three-attribute goods the rankings across attributes of the intensity of search correspond to the prediction of optimization. Also, the order in which attributes are inspected is as it would be if the order were chosen in order to maximize expected return (strictly speaking we infer this latter conclusion from responses to a closely related question).

Additionally, when the observed behavior differed with strict optimizing behavior, the differences were uniform across subject pools and corresponded roughly to a simple satisficing strategy. That is, subjects in our experiments responded to changing costs of information as if they had simplified the first-order conditions to make them easier to handle. Specifically, the behavior suggests that when responding to change in information costs the subjects ignored the sequential and simultaneous aspects of the solution.

TABLE 19: t-Statistics for Comparative Statics

3A: $\sum X_1 = [0,8], \sum X_2 = [0,8], \sum X_3 = [0,8]$

MTSAC				PCC			
	Δc_1	Δc_2	Δc_3		Δc_1	Δc_2	Δc_3
$\Delta \bar{y}_1$	1.51	.10	.15	$\Delta \bar{y}_1$	2.92	.01	.01
$\Delta \bar{y}_2$.36	1.07	.66	$\Delta \bar{y}_2$.91	1.70	.14
$\Delta \bar{y}_3$.72	.35	.03	$\Delta \bar{y}_3$	1.00	.94	1.83
CSUN				UCLA			
	Δc_1	Δc_2	Δc_3		Δc_1	Δc_2	Δc_3
$\Delta \bar{y}_1$	3.71	.06	.25	$\Delta \bar{y}_1$	6.06	.35	.32
$\Delta \bar{y}_2$.95	3.71	.56	$\Delta \bar{y}_2$.95	3.82	.05
$\Delta \bar{y}_3$.55	.88	2.39	$\Delta \bar{y}_3$	1.17	1.35	4.58

3B: $\sum X_1 = [0,5], \sum X_2 = [0,10], \sum X_3 = [0,10]$

MTSAC				PCC			
	Δc_1	Δc_2	Δc_3		Δc_1	Δc_2	Δc_3
$\Delta \bar{y}_1$.44	.07	.11	$\Delta \bar{y}_1$	1.43	.60	.21
$\Delta \bar{y}_2$.40	1.46	.48	$\Delta \bar{y}_2$.16	1.51	.10
$\Delta \bar{y}_3$	1.15	.85	1.69	$\Delta \bar{y}_3$.79	1.37	1.87
CSUN				UCLA			
	Δc_1	Δc_2	Δc_3		Δc_1	Δc_2	Δc_3
$\Delta \bar{y}_1$	2.15	.11	1.09	$\Delta \bar{y}_1$	2.15	.09	.03
$\Delta \bar{y}_2$.06	3.50	.20	$\Delta \bar{y}_2$	1.16	4.43	.04
$\Delta \bar{y}_3$.48	1.00	2.10	$\Delta \bar{y}_3$.41	1.05	4.17

c_i = sampling cost on attribute i ; \bar{y}_i = average cutoff level on attribute i

TABLE 20: t-Statistics for Decreasing Cutoff Levels

2A: $\sum X_1 = [1,11], \sum X_2 = [1,11]$

Group	\bar{y}_1 vs \bar{y}_2
MTSAC	2.63
PCC	2.70
CSUN	3.81
UCLA	5.20

3A: $\sum X_1 = [0,8], \sum X_2 = [0,8], \sum X_3 = [0,8]$

Group	$c_1 = .10, c_2 = .10, c_3 = .10$	
	\bar{y}_1 vs \bar{y}_2	\bar{y}_2 vs \bar{y}_3
MTSAC	1.85	1.09
PCC	2.26	.21
CSUN	1.77	1.37
UCLA	3.26	.46

c_i = sampling cost on attribute i

\bar{y}_i = average cutoff level on attribute i

TABLE 23. Complete Summary Results for Three-Attribute Equal Intervals Problems: Means and Variance of Observed Cutoff Levels

$$3.A: \sum X_1 = [0,8], \sum X_2 = [0,8], \sum X_3 = [0,8]$$

#	N	c_1	c_2	c_3	\bar{y}_1	\bar{y}_2	\bar{y}_3	σ_1^2	σ_2^2	σ_3^2
MTSAC										
1	33	.10	.10	.10	3.88	2.93	2.44	4.99	3.47	3.01
2	33	2.00	.10	.10	3.06	2.77	2.79	4.43	2.74	4.37
3	33	.10	2.00	.10	2.93	2.45	2.60	4.54	2.85	3.51
4	33	.10	.10	2.00	3.96	3.24	2.43	4.27	3.71	3.90
PCC										
1	30	.10	.10	.10	4.69	3.39	3.27	4.91	4.68	4.77
2	30	2.00	.10	.10	2.99	2.88	2.72	4.88	4.26	4.05
3	30	.10	2.00	.10	4.68	2.49	2.73	6.26	3.38	4.69
4	30	.10	.10	2.00	4.69	3.31	2.25	5.35	4.77	4.18
CSUN										
1	22	.10	.10	.10	5.08	4.00	3.16	4.19	3.66	4.22
2	22	2.00	.10	.10	2.85	3.43	2.83	3.38	4.06	3.19
3	22	.10	2.00	.10	5.12	2.03	2.61	4.90	2.29	3.99
4	22	.10	.10	2.00	5.25	3.66	1.79	6.05	4.23	2.70
UCLA										
1	43	.10	.10	.10	5.36	3.95	3.75	4.14	3.72	4.39
2	43	2.00	.10	.10	2.86	3.56	3.22	2.99	3.52	4.33
3	43	.10	2.00	.10	5.21	2.42	3.17	3.47	3.04	3.44
4	43	.10	.10	2.00	5.22	3.93	1.90	3.70	3.40	2.49

c_i = sampling cost on attribute i

\bar{y}_i = average cutoff level on attribute i

σ_i^2 = sample variance

TABLE 24. Complete summary Results for Three-Attribute Unequal Intervals Problems: Means and Variances of Observed Cutoff Levels

$$3.B: \sum X_1 = [0,5], \sum X_2 = [0,10], \sum X_3 = [0,10]$$

#	N	c_1	c_2	c_3	\bar{y}_1	\bar{y}_2	\bar{y}_3	σ_1^2	σ_2^2	σ_3^2
MTSAC										
1	33	.10	.10	.10	2.55	3.50	3.73	1.81	4.65	7.87
2	32	.75	.10	.10	2.40	3.74	2.96	1.65	6.13	6.32
3	33	.10	3.50	.10	2.58	2.71	3.16	2.01	4.61	6.60
4	32	.10	.10	3.50	2.52	3.25	2.63	1.53	4.16	5.59
PCC										
1	30	.10	.10	.10	2.76	4.11	4.15	1.82	8.53	9.32
2	30	.75	.10	.10	2.24	3.99	3.56	1.95	7.22	7.06
3	30	.10	3.50	.10	2.54	2.99	3.13	2.11	7.53	6.80
4	30	.10	.10	3.50	2.69	4.18	2.75	2.12	7.93	6.95
CSUN										
1	22	.10	.10	.10	3.11	4.90	3.78	2.22	7.69	7.79
2	21	.75	.10	.10	2.17	4.94	4.17	1.68	3.39	5.90
3	22	.10	3.50	.10	3.06	2.29	2.97	2.04	3.98	5.82
4	22	.10	.10	3.50	2.60	4.73	2.16	2.54	7.18	4.67
UCLA										
1	43	.10	.10	.10	3.06	5.23	4.38	1.66	5.93	6.05
2	43	.75	.10	.10	2.46	4.61	4.16	1.67	5.73	5.49
3	43	.10	3.50	.10	3.04	3.00	3.79	1.22	4.70	6.95
4	43	.10	.10	3.50	3.05	5.20	2.40	1.38	5.16	3.37

c_i = sampling cost on attribute i

\bar{y}_i = average cutoff level on attribute i

σ_i^2 = sample variance

TABLE 26: Counts Indicating Direction of Change in Cutoff Levels

Group	3A									3B								
	Δy_1			Δy_2			Δy_3			Δy_1			Δy_2			Δy_3		
	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-
	$\Delta c_1 > 0$									$\Delta c_1 > 0$								
MTSAC	8	7	18	10	12	11	10	13	10	8	11	13	14	10	8	7	11	14
PCC	5	7	18	7	11	12	6	10	14	6	11	13	9	14	7	4	15	11
CSUN	1	3	18	6	6	10	7	5	10	1	3	17	6	7	8	8	6	7
UCLA	1	6	36	12	11	20	5	14	24	7	13	23	10	11	22	11	10	22
	$\Delta c_2 > 0$									$\Delta c_2 > 0$								
MTSAC	13	11	8	6	9	17	8	14	11	11	10	11	9	6	17	10	11	11
PCC	9	11	10	6	11	13	8	11	11	6	15	9	7	8	15	7	9	14
CSUN	5	9	8	4	0	18	6	5	11	6	8	8	0	4	18	3	7	12
UCLA	7	13	23	6	6	31	10	7	26	10	21	12	7	6	30	9	12	22
	$\Delta c_3 > 0$									$\Delta c_3 > 0$								
MTSAC	11	9	11	16	11	6	8	11	14	9	12	11	10	11	11	7	8	17
PCC	4	15	9	10	12	8	5	11	14	8	15	7	8	15	7	6	9	15
CSUN	6	9	7	6	5	11	2	4	16	3	8	11	9	7	6	3	5	14
UCLA	8	19	16	15	12	16	3	10	30	9	24	10	15	15	13	4	7	32

c_i = sampling cost on attribute i

y_i = cutoff level on attribute i

seven items generated were below your cutoff level, but that the next one was above the cutoff. Your payment would be the amount of the last item generated (the eighth) minus eight times the cost of generating an item.

First, we shall ask you to select one individual as a monitor to watch the procedures, to examine the equipment, and to make sure that the the experimenters really are doing what they say they are doing. The monitor should check the truthfulness of what the experimenter says, but other than that may not communicate any information to you in any way. If the monitor communicates any other information, he or she will be asked to leave without payment. The monitor will receive \$_____.

(pick volunteer)

INSTRUCTIONS

PART TWO

The two-attribute problem is similar to the single-attribute problem. Two-attribute items are described by two numbers, a level of attribute 1 and a level of attribute 2. The rule for selecting a two-attribute item works much like that for selecting a single-attribute item. You must choose a cutoff level for attribute 1 and a cutoff level for attribute 2. As before, these will determine the smallest levels that you can receive for each attribute.

Once you have set cutoff levels for each attribute, we will begin searching for an item by generating levels for attribute 1 (again using the bingo cage). As before, we will generate items until one is found which has a level of attribute 1 in excess of your cutoff level for attribute 1. Each time an item is rejected and a new one is generated, you will be charged a fixed amount. Once an accepted level for attribute 1 has been found, we will generate a single level for attribute 2. You will also be charged a fixed amount for this, although it may differ from the cost for generating levels of attribute 1. If the level of attribute 2 is less than your cutoff level for attribute 2, the entire item will be rejected and a new item generated starting with attribute 1. In other words, if the level of attribute 2 is below your cutoff level, you must begin your search for an item with attribute 1—in the two-attribute problem, each attribute must exceed its cutoff level in order that the item be acceptable.

your cutoff level, you must begin your search for an item with attribute 1—in the three-attribute problem each attribute must exceed its cutoff level in order that the item be accepted. Otherwise, you start over. However, the costs for generating levels of each attribute will still be charged to you. Thus, your payoff in the three-attribute problem is the sum of the final values generated for each attribute, less the costs of generating all the numbers needed to find an accepted item.

Example:

1. Three draws required to get an accepted level of attribute 1.
2. First draw on attribute 2 below its cutoff level.
3. Five draws required to get another accepted level for attribute 1.
4. One draw for attribute 2, again below cutoff level.
5. Two draws needed to get new attribute 1.
6. One draw for attribute 2—above cutoff level—accepted.
7. One draw for attribute 3—rejected.
8. Four draws to get an accepted level of attribute 1.
9. One draw for attribute 2—accepted.
10. One draw for attribute 3—accepted.

Your payoff would be the last value generated at step 8 plus the value generated at step 9 plus the value at step 10 minus fourteen times the cost of generating a first attribute (cost 1) minus four times the cost of generating a second attribute (cost 2) and minus two times the cost of generating a third attribute (cost 3).

SAMPLE FORMS USED BY SUBJECTS

ONE ATTRIBUTE

Name _____

Social Security No. _____

Subject Number _____

Decision No. _____

Attribute	Minimum Possible Value	Maximum Possible Value	Cost: C	Cutoff Level	Number of draws: N	Final Value: V
1						

Att.	V	-	C	x	N	=	earnings
1							

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