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Rational, Repetitive Choice: The Discrimination Model versus the Camilleri-Berger Model

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The best-known model of rational, repetitive choice in sociology is the Camilleri-Berger Model. The Discrimination Model is a recent competitor to the Camilleri-Berger Model and a thorough comparison is called for. In this paper, the two models are presented and compared in some detail with regard to the way they handle utility and marginal utility; the way they explain (or fail to explain) matching; their cognitive assumptions; their heuristic capabilities for application to social situations; and their predictive accuracy. The Discrimination Model comes out favorably on all counts. In addition, it is a "deeper" theory because it can specify the conditions under which the Camilleri-Berger Model will furnish accurate predictions.

INTRODUCTION

The Discrimination Model of rational, repetitive choice (Lindenberg, 1980) is built on the shoulders of the Siegel-Ofshe model (Siegel et al., 1964; Ofshe and Ofshe, 1970). Its most important features are the following: (1) it represents restraints on gain maximization; (2) it stresses marginal utility as governing choice behavior; (3) it discourages lists of rewards in favor of global utility components; and (4) for many situations of more than two alternatives, it assumes that individuals arrive at choice proportions through pairwise comparison of alternatives.

The Camilleri-Berger model of rational repetitive choice (Camilleri and Berger, 1967) may be said to be the best-known model of this kind in sociology and it is embedded in an impressive research program.[1] Since this model is opposed to the discrimination model on all important points, a thorough comparison seems called for. Balkwell (1976) has already compared the Siegel-Ofshe model with the Camilleri-Berger model in this journal. He found faults with both models and could not conclusively disconfirm either, though his comparison favored the Siegel-Ofshe model. Since the discrimination model differs even more from the Camilleri-Berger model, and since its central ideas are based on the Siegel-Ofshe model, a more conclusive comparison may be possible and will be attempted in this paper.

Before presenting the two models, it should be mentioned where they are in complete agreement: both assume exclusive alternatives and event probabilities attached to elementary outcomes, utility maximizing, and stable state choice probabilities (i.e., choice is said to correspond to a stationary stochastic process).

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[1] This program is linked to the expectation states research program. See, for example, Balkwell, 1969; Camilleri et al., 1972; Kervin, 1974; Camilleri and Conner, 1976. Outside this program see McMahon and Camilleri (1975) for an interesting application. More recently, a different model has been developed for expectation states (see Berger et al., 1977; Webster and Driskell, 1978; Fox and Moore, 1979). Since it is not a general repetitive choice model, it will not be discussed in this paper. The McMahon and Camilleri (1975) data involve interesting new aspects: the experiment runs over several weeks, the decision-making process involves collective goods, and the dependent variable is the rate of participation in the decision-making process over time. The authors do not explain the data but attempt to fit the CB model to the data. Because the experiment entails participation over an extended period of time, a theory of participation costs has to be added for the *explanatory* application of either model. This goes beyond the purpose of this paper and will be dealt with in a separate publication on collective goods and participation.

THE MODELS

The Discrimination Model: The Two-Alternative Case

For reasons of exposition, the two-alternative model will be presented first. The central concept of the model is "discrimination," viz. the deviation of choice proportions from .5 (the point at which no distinction between the alternatives is made in terms of choice). It is assumed that there is both utility and disutility connected with discrimination: the expected utility of discrimination ($E(U_d)$) and the disutility of discrimination (DU_d).[2] Let $E(U_s)$ stand for the expected utility of a strategy (a probability vector (P_1,P_2)), then the maximand is:

$$E(U_s) = E(U_d) - DU_d \qquad (1)$$

By itself, $E(U_d)$ is equivalent to the expected gain from a strategy for $P_1>.5$, because gain is maximized if the choice probability for the highest expected reward is unity (maximal discrimination or "pure" strategy). The disutility (DU_d) thus is a restraint on gain maximization.

How are these components defined?

$$\begin{aligned} E(U_d) &= ag_1P_1 + ag_2\ (1 - P_1) \\ &= a\ (g_1 - g_2)\ P_1 + ag_2 \end{aligned} \qquad (2)$$

where

- a = marginal utility of reward g;
- g_i = the sum of rewards and costs of the i^{th} alternative, each weighted by the appropriate event probability π ($i = 1, 2$);
- P_i = stable state probability of choosing the i^{th} alternative ($i = 1, 2$).

$$DU_d = (P_1 - .5)^2 \qquad (3)$$

This disutility expression is based on the idea of a *global* disutility of discrimination in which all possible motives that turn against gain maximization are aggregated (see Lindenberg, 1980:298ff.). This idea is translated into the following: let x be a point such that $P_i>x$ and interpret x as a reference point for an ideally *maximal* deviation from nondiscrimination, then P_1-x is proportional to the disutility corresponding to this reference point. For example, for a situation in which strategies have distributional effects on self and others, equality may be connected with $x=.5$, equity with $x=.7$, and charity with $x=.9$. Rather than list these motives as separate utility components, which would lead to arbitrary ad hoc lists and problems of commensurable measurements, one can aggregate over all the motives (i.e., reference points). Individuals are likely to have an idiosyncratic scatter of these motives, and with aggregate data a *global* disutility is more likely to capture the joint effect of these scatters. Mathematically, the aggregation is simple: let $P_1\geq.5$ and $P_2\leq.5$ and $P_1+P_2=1$, then

$$\begin{aligned} DU_d &= \int_{.5}^{P_1} (P_1 - x)\ dx + \int_{P_2}^{.5} (x - P_2)\ dx \\ &= (P_1 - .5)^2 \end{aligned} \qquad (4)$$

Thus, equation (1) turns into

$$E(U_s) = a(g_1 - g_2)\ P_1 + ag_2 - (P_1 - .5)^2 \qquad (5)$$

Since the individual is said to maximize utility, we are now looking for the strategy that will maximize $E(U_s)$. This will be the case where the individual cannot increase $E(U_s)$ any more by increasing P_1, i.e., where the marginal utility of P_1 (MU_p) is zero:

$$MU_p = \frac{d\ (E(U_s))}{dP_1} = 0 \qquad (6)$$

This point is uniquely determined by the following equation:

$$P_1 = \frac{a}{2}\ (g_1 - g_2) + .5 \qquad (7)$$

Equation (7) is the prediction equation if a is known or estimated. The assumption of a stable state (or stationary stochastic process) leads, ceteris paribus, to the assumption that a, the marginal utility of the reward, is also stable in a repetitive choice situation. With the added assumption that a in a new but comparable situation is the same as in the original situation, a for the

[2] The disutility is not "expected" because it solely depends on the chosen strategy and is therefore not directly dependent on any event probability.

new situation can be estimated[3] on the basis of P_1 in the original situation:

$$a = \frac{2\,(P_1 - .5)}{g_1 - g_2} \tag{8}$$

Observe that there is no separate weight assigned to the disutility. Every change in the weight of the disutility expresses itself in a change of the marginal utility a. For this reason, there is also no problem of commensurable measurement of the utility components: a expresses the relation of the first to the second (thus a also adapts to the scale of the reward, since DU_d is fixed in scale). For example, if somebody's feelings of charity are increased, then a will decrease, expressing a larger weight for DU_d. If, on the other hand, somebody is badly in need of the reward, a will increase *thereby* lowering the weight of DU_d.

The model thus argues against lists of inhomogeneous rewards and costs. Indeed, it distinguishes two utility components, one of which is already global (DU_d) and one of which should be expressed in terms of a homogeneous good or as a basket of goods to which a number can be assigned.

The General Discrimination Model

The simultaneous model. The general discrimination model (see Lindenberg, 1980:306–307) is:

$$E(U_s) = a\sum_{i=1}^{k} g_i\,P_i - \tfrac{1}{2}\sum_{i=1}^{k}\left(P_i - \frac{1}{k}\right)^2 \tag{9}$$

where k = number of alternatives.

[3] Note that a can also be expressed as $a = (P_i - 1/k)/(g_i - \bar{g})$. This makes it even easier to interpret a: the numerator is the difference between P_i and the average P $(=1/k)$ and the denominator is the difference between g_i and the average g $(=\bar{g})$. Since discrimination is connected with costs from the DU_d component, a expresses the willingness to bear the costs for a certain amount of discrimination $(P_i - 1/k)$, given a certain amount of gain opportunity $(g_i - \bar{g})$.

It is obvious that a should be estimated on the basis of the largest available $g_i - \bar{g}$, because as $g_i - \bar{g}$ approaches zero, small differences in gain opportunity become psychologically less and less meaningful while they acquire a larger and larger influence on a. If possible, negative gain opportunity should be avoided for estimation because the choice of strategy is likely to begin with the largest $g_i - \bar{g}$, as can be seen below from the general sequential discrimination model.

The strategy that maximizes $E(U_s)$ is the one for which the marginal utility of all P_i is zero. This point is uniquely determined by

$$P_i = \frac{a}{k}\left(kg_i - \sum_{j=1}^{k} g_j\right) + \frac{1}{k} \tag{10}$$

and

$$a = \frac{k\left(P_i - \frac{1}{k}\right)}{kg_i - \sum_{j=1}^{k} g_j} \tag{11}$$

This general model assumes that individuals act "as if" they could arrive at all the P_i simultaneously, which involves solving a Lagrangian expression. Are the cognitive "as if" capabilities of individuals not overrated by this assumption? The possibility that this is so has led to yet another general model (Lindenberg, 1980:307–308).

The sequential model. Cognitive studies suggest that not every point in an evaluated ordering is cognized as easily as any other. Since expected rewards also form an ordering, the same can be said for them. The anchors (the best and the worst) are most easily cognized and the lowest (worst) anchor forms the most stable point of comparison. The second best is more difficult to cognize than the anchors but easier than the third best, etc. (see Lindenberg, 1977). This suggests that in case of more than two alternatives, choice probabilities are established stepwise by a comparison of the expected rewards for the anchors, then by a comparison of the second highest expected reward with the lowest, etc. In formal language, the general model looks as follows: G is an ordering of the rewards such that $g_1 \geq g_2 \geq g_3 \ldots g_{k-1} \geq g_k$. Then

$$P_1 = \frac{a}{2}(g_1 - g_k) + \tfrac{1}{2}$$

$$P_2 = \frac{a}{2}(g_2 - g_k) + \frac{1 - P_1}{2}$$

$$P_3 = \frac{a}{2}(g_3 - g_k) + \frac{1 - P_1 - P_2}{2}$$

$$\vdots$$

$$P_k = 1 - P_1 - P_2 \ldots - P_{k-1} \tag{12}$$

or generally:

$$P_i = \frac{a}{2}(g_i - g_k) + \frac{1 - \sum_{j=1}^{i-1} P_j}{2} \qquad (13)$$

$$P_k = 1 - \sum_{j=1}^{k-1} P_j$$

$$a = \frac{2\,(P_1 - .5)}{g_1 - g_k} \qquad (14)$$

Comparison of the General Discrimination Models

While both models performed satisfactorily in a test with available data (Lindenberg, 1980:308ff.), the sequential model did considerably better. For this reason and because of its conceptual qualities, it was adopted as *the* general discrimination model. Yet, the sequential model requires a cognitively prominent ordering (such that $P_1 \geqslant .5$) and an evaluated ordering; in other words, the sequential model is *only* applicable if both of the following conditions are met: (a) the choice situation entails explicit rewards; (b) the most attractive alternative is clearly prominent.

It is relatively easy to determine when a choice situation entails explicit rewards and it is not difficult to establish a post hoc criterion for "clearly prominent":

$$a\,(kg_1 - \sum_{j=1}^{k} g_j) \geqq \frac{k}{2} - 1$$
$$\text{(with } a \text{ as in eq. 11)} \qquad (15)$$

But it is difficult to find *theoretical* criteria for "clearly prominent" and the formulation of such criteria must be left as a problem for further study. By the post hoc criterion, all the experiments dealt with in this paper (except where explicitly noted otherwise) meet the conditions for the sequential model.

The Camilleri-Berger (or CB) Model

Due to the fact that the CB model does not represent restraints on gain maximization, it is much simpler than the discrimination model. The basic idea underlying the model is the following: individuals distribute their choice frequencies over the alternatives proportionately to the expected utilities of the alternatives. Let P_1 and P_2 be the choice probabilities and let EU_1 and EU_2 be the expected utilities of alternative (1) and alternative (2), respectively, then $P_1/P_2 = EU_1/EU_2$. Homans (1974:31) has formulated a very similar theory. Problems arise when negative utilities occur, because then proportionality cannot be applied. In order to solve this problem, Camilleri and Berger introduced what they called "expected positive utility" (symbolized G). Negative elementary outcomes in one alternative are taken to be positive outcomes for all other alternatives. In this way, expected utility must always be positive and the idea of proportionality can be applied to all cases. However, this is more than a technical adjustment. In fact, contrary to other decision-making theories, this model implies that costs and benefits of one alternative are not weighed against each other; rather, the benefits of one alternative are increased by the costs of all other alternatives. Thereby the relative weight of alternatives is affected and the original idea of proportionality has acquired different consequences. For example, let the "normal" expected utilities for two alternatives be $EU_1 = 11-8$ and $EU_2 = 1$; then the original idea of proportional choice frequencies would lead to the prediction $P_1 = .75$ and $P_2 = .25$. The calculation of expected positive utilities, however, leads to $G_1 = 11$ and $G_2 = 1 + 8$, and therefore $P_1 = .55$ and $P_2 = .45$, a sizable difference in prediction.

Formally, the CB model has been presented as follows (Balkwell, 1976): let there be m alternatives; let p_i denote the sum of elementary gains for alternative i (i=1,2. . .k); let q_i denote the sum of the absolute values of elementary losses for alternative i (both elementary gains and losses are assumed to be weighted by their subjective probabilities of occurrence); and let $g_i = p_i - q_i$. Then the expected positive utility of alternative i is

$$G_i = g_i + \sum_{j=1}^{k} q_j \qquad (i = 1, 2 \ldots k) \ (16)$$

$$P_i = G_i \,/ \sum_{j=1}^{k} G_j$$

Thus, the expected positive utility is equal to the "normal" expected utility (g_i) plus a nonnegative constant. The general prediction equation follows from the proportionality idea:

$$P_i = \frac{g_i + \sum_{j=1}^{k} q_j}{\sum_{j=1}^{k} (g_j + kq_j)} \qquad (17)$$

If and only if $\Sigma q_j = 0$, then this model is identical to Homans's (1974:31) theory of proportional choice frequencies, because then there is no difference between G and EU.

COMPARISON OF BASIC ASPECTS OF THE TWO MODELS

In the following sections, the models will be compared with regard to aspects that differentiate them directly: the way they handle utility and marginal utility; the way they explain (or fail to explain) matching; and the different cognitive processes they imply.

Utility and Marginal Utility

The CB model is clearly "subjectivist" in the sense that it makes use of expected *utility* rather than expected *value*. For instance, not money but the utility of money would be the basis for calculating G. However, in many possible cases of application, the CB model implies that utility has no influence on choice frequencies. This is the case when two conditions are met: first, quantities of costs and benefits pertain to one and the same measurable good (as is the case with money) or basket of goods; second, the marginal utility of the homogeneous good or basket of goods can be assumed to be stable for the period under investigation. Then the CB model needs no assumptions on utility functions and factually works with expected value rather than expected utility. To show this, let the marginal utility of the homogeneous good g be $MU_g = dU_g/dg = a$; then the utility of a particular amount of g is $U_g = ag$. Since a is by assumption constant, it is a multiplier of all G's in the CB model and thus cancels out, no matter what its value.

The advantage of this circumstance is obvious: it makes the model simple and easy to apply. But if utility and marginal utility do affect the distribution of choice probabilities, then the CB model cannot consider this effect and will produce predictions that are sometimes right and sometimes wrong, depending on the actual value of the marginal utility. In order to analyze this aspect, the following procedure was chosen. The discrimination model, which does consider marginal utility, is for the time being taken to be a descriptive rather than a predictive tool. On this basis a particular value of a is interpreted as the "true" a if it produces the observed P when used in the model. Then, the question is asked: when are the descriptions by the two models identical? In this way, it is possible to say whether or not marginal utility affects choice probabilities. To simplify the analysis, the two-alternative case is used.

The two models yield identical results if the following equation holds:

$$\frac{a}{2}(g_1 - g_2) + .5 = \frac{G_1}{G_1 + G_2}. \qquad (18)$$

From this, we get by regrouping:

$$a(g_1 - g_2) = \frac{G_1 - G_2}{G_1 + G_2} \qquad (19)$$

Since $G_1 - G_2 = g_1 + \Sigma q_j - g_2 - \Sigma q_j = g_1 - g_2$ (see equation 16),

$$a = \frac{1}{G_1 + G_2} \qquad (20)$$

In words, the two models will yield identical results if the (true) marginal utility is equal to the inverse of the sum of the expected positive utilities of both alternatives.[4] This amounts to an implicit hypothesis of the CB model that the marginal utility of g depends solely on the reward schedule, such that the marginal utility of g is always equal to $1/(G_1+G_2)$ and can therefore be neglected as a separate factor. How well does this hypothesis stand

[4] For the k-alternative case, this holds only for the simultaneous model.

up to test? Various experiments by Siegel et al. (1964) and by the Ofshes (1970) meet the relevant test conditions: homogeneous good (money), a stable marginal utility, and a two-alternative choice situation.

The experimental setup in Siegel's case was as follows: two lights came on with fixed probabilities (π_1 and $1-\pi_1$) and the subjects guessed beforehand which light it would be by pressing one of two buttons. Rewards were given for a correct choice and in some cases "punishments" were levied for an incorrect choice. In the Ofshe experiments, a subject was asked to choose one of two "persons" as a coalition partner. Unknown to the subject, these "persons" were computer robots who, in turn, chose the subject as a partner according to fixed probabilities (π_1 and $1-\pi_1$). Rewards were given to the subject if he or she happened to choose a coalition partner who reciprocated the choice. The reward schedules for both the Siegel and the Ofshe choice situations are summarized in Table 1, where the r's represent rewards and costs in cents. Some of these experiments and their results are presented in Table 2. It can be seen that the marginal utility a, calculated according to equation 8, indeed closely follows $1/(G_1+G_2)$. The last column shows the absolute discrepancies (d) between the observed and the CB-predicted probabilities. In all cases, d is very small, i.e., the predictions are very good ($\bar{d}=.009$). It seems that the implicit CB-hypothesis about marginal utility can stand up to test.

This result contradicts the very basis of the discrimination model, viz. the assumption that the marginal utility of g is *not* determined by the reward schedule and should therefore be explicitly introduced as an open parameter. The Ofshes addressed themselves directly to this issue by attempting to manipulate the marginal utility *without* changing the reward schedule. Did they succeed? They had two experimental setups, identical except for the instructions. In one setup, the subjects were asked to win as much money as they could (let us call this "high marginal utility" [MU] condition). In the other setup (low MU condition), the subjects were not asked to maximize money return; instead, they were urgently reminded that those who were systematically excluded from coalitions would win almost nothing in the entire session, and they were told that they would meet the other players afterwards for discussion (Ofshe and Ofshe, 1970:35, 51–52). The results for male and female groups of subjects are shown in Table 3. The CB predictions are quite poor ($\bar{d}=.121$) and it is clear from these results that the marginal utility *can* be manipulated without changing the reward schedule. The highest a (.4375) is more than three times the lowest a (.1333) for the *same* reward schedule. The implicit CB hypothesis surely does not hold generally. This conclusion is strengthened by

Table 1. Scheme of Choice Situations for Various Experiments by Siegel et al. and Ofshe and Ofshe

		events	
		π_1	π_2
alternatives	1	r_{11}	r_{12}
	2	r_{21}	r_{22}

Table 2. Summary of Various Experiments, Their Results, and the Absolute Discrepancy (d) between Observed and CB-Predicted Probabilities

Experiment	π_1	π_2	r_{11}	r_{12} r_{21}	r_{22}	obs. P_1	a	$1/(G_1+G_2)$	$a(G_1+G_2)$	d
1*	.75	.25	5	0	5	.7700	.2160	.2000	1.080	.020
2**	.80	.20	5	0	10	.6716	.1716	.1667	1.029	.004
3**	.70	.30	5	0	10	.5396	.1572	.1538	1.022	.000
4**	.60	.40	5	0	10	.4397	.1206	.1428	0.845	.011
								Average Abs. Discrepancy		.009

* Siegel et al. (1964:49).
** Ofshe and Ofshe (1970:80ff.).

Table 3. Summary of Two Ofshe Experiments, Their Results, and the Absolute Discrepancies (d) between Observed and CB-Predicted Probabilities

π_1	π_2	r_{11}	r_{12} r_{21}	r_{22}	Condition	sex	obs. P_1	a	$1/(G_1+G_2)$	$a(G_1+G_2)$	d
.70	.30	5	0	5	High MU	male[a]	.8495	.3495	.2	1.747	.150
						female[b]	.9375	.4375	.2	2.187	.238
					Low MU	male[c]	.6727	.1727	.2	0.864	.027
						female[d]	.6333	.1333	.2	0.667	.067
									Average Abs. Discrepancy		.121

[a] Ofshe and Ofshe (1970:69).
[b] Ofshe and Ofshe (1970:70).
[c] Extracted from Ofshe's data (Ofshe and Ofshe, 1970:183), trial 71–100.
[d] Extracted from Ofshe's data (Ofshe and Ofshe, 1970:184), trial 41–100.

results from still other Siegel and Ofshe experiments, summarized in Table 4. Almost all CB predictions are very poor ($\bar{d}=.125$) and a differs considerably from $1/(G_1+G_2)$ in all cases.

Why then did the CB model predict the data in Table 2 so well? There is no obvious answer to this question, but the following may be a fruitful attempt to find an answer. It seems that a is not *totally* independent of $1/(G_1+G_2)$. First, the correlation between a and $1/(G_1+G_2)$ is sizable (.56). Second, the ratio of a to $1/(G_1+G_2)$ is quite well behaved (see Tables 2–4), with a mean of 1.46. Third, in almost all cases $a>1/(G_1+G_2)$; the exceptions are the experiments in which a was intentionally manipulated to be low (see Table 3) and experiment 4 in Table 2. A careful conclusion from these relationships is that $1/(G_1+G_2)$ acts as a sort of anchor for a. If the experimental circumstances are not particularly motivating or demotivating towards g (as was perhaps the case with the experiments summarized in Table 2), then a will be close to $1/(G_1+G_2)$. In order to bring a below the level of $1/(G_1+G_2)$, a special effort has to be made to reduce the marginal utility (see Table 3). In order to raise a considerably above the level of $1/(G_1+G_2)$, the experimental situation must be particularly motivating (see Table 4). For example, without commenting on the difference, Siegel et al. (1964:46–47,101) used different instructions for experiment 1 in Table 2 and experiments 5–7 in Table 4. In the first case, they said to the subjects: "if you play carefully you should come out winning at the end of the session." In the other cases, they said: "if you play carefully you should end the session with a considerable amount of money which would be yours to keep." The second instruction seems more motivating

Table 4. Summary of Various Experiments, Their Results, and the Absolute Discrepancies (d) between Observed and CB-Predicted Probabilities

Experiment	π_1	π_2	r_{11}	r_{12} r_{21}	r_{22}	obs. P_1	a	$1/(G_1+G_2)$	$a(G_1+G_2)$	d
1[a]	.70	.30	5	0	5	.8250	.3250	.2	1.625	.125
2[a]	.30	.70	5	0	5	.1562	.3031	.2	1.515	.103
3[b]	.60	.40	5	0	5	.6750	.3500	.2	1.750	.075
4[b]	.60	.40	5	0	5	.7250	.4500	.2	2.250	.125
5[c]	.75	.25	5	−5	5	.9250	.1716	.1	1.716	.179
6[d]	.70	.30	5	−5	5	.8630	.1810	.1	1.810	.162
7[c]	.65	.35	5	−5	5	.7530	.1687	.1	1.687	.103
								Average Abs. Discrepancy		.125

[a] Experiments (1) and (2) were performed on the same subjects by reversing the event probabilities after 50 trials (see Ofshe and Ofshe, 1970:72ff.).
[b] Experiment (3) was performed with male subjects, experiment (4) with female subjects (see Ofshe and Ofshe, 1970:69f.).
[c] Siegel et al. (1964:106ff.).
[d] Siegel et al. (1964:115).

than the first, and $a(G_1 + G_2) = 1.08$ in the first case, while it varies between 1.69 and 1.81 in the second case.[5]

In sum, the implicit hypothesis of the CB model, viz. that the marginal utility of g is determined by the reward schedule, did not stand up to test. It seems clear from the review of fifteen experiments that the marginal utility of g should be introduced as an open parameter, as is done in the discrimination model. Yet, the CB model may have provided the discrimination model with a standard for the marginal utility such that values of $a << 1/(G_1 + G_2)$ can be viewed as particularly low and values of $a >> 1/(G_1 + G_2)$ can be considered particularly high, at least for experimental situations.

Matching

Siegel et al. observed that matching between event and choice probabilities tends to occur "when subjects receive no special payoff for a correct choice" (1964:53). How can this be explained? In terms of the discrimination model, the explanation is possible and runs as follows. Given that a choice can be either "right" or "wrong" in the eyes of the chooser; given that no *other* (material or immaterial) benefits and/or costs are connected to the choice of alternatives; and given that the event probabilities add up to unity; then the chooser will register rewards and utility of "being right" by simple count: each correct choice adds one count to the total reward (which equals the total utility of "being right"). Because there are no explicit rewards, the ordering of g's is not evaluated and therefore the simultaneous model applies (eq.10). On this basis, matching is predicted for just the kind of situation Siegel observed:

$$P_i = \frac{a}{k}(kg_i - \sum_{j=1}^{k} g_j) + \frac{1}{k} \qquad (10)$$

$$g_i = \pi_i;\ \sum_{j=1}^{k} g_j = \sum_{j=1}^{k} \pi_j = 1;\ a = 1;$$

$$P_i = \frac{1}{k}(k\pi_i - 1) + \frac{1}{k} = \pi_i. \quad \text{Q.E.D.}$$

Matching can also occur in other circumstances in which $\Sigma\pi_i = 1$, as long as $a(kg_i - \Sigma g_j) = k\pi_i - 1$. It is unlikely that $a(kg_i - \Sigma g_j)$ just happens to be equal to $k\pi_i - 1$. In other words, aside from the conditions listed above, matching will not be frequently predicted by the discrimination model.

Things are different with the CB model. First, there is no *explanation* for matching. Second, the model predicts matching generally whenever $G_i = \pi_i \Sigma G_j$, and this condition is easily met. For example, for the two-alternative case, whenever $r_{11}, r_{22} > 0$ and $r_{12}, r_{21} \leq 0$ and $r_{11} + |r_{21}| = r_{22} + |r_{12}|$, matching will be predicted. These conditions are met in no less than twelve out of the fifteen experiments reported above (the exceptions are experiments 2–4 in Table 2). The average absolute discrepancy between the observed and the CB-predicted probabilities for these cases is $\bar{d} = .115$, with a standard deviation of $s = .06$. This performance is very poor and, clearly, the CB model's implications for matching are highly dubious.

Cognitive Processes

The two models imply at least two different kinds of cognitive processes. First, the organization of information on alternatives: The discrimination model assumes that individuals arrive at expected utility by considering costs and benefits separately for each alternative; the CB model assumes that individuals use the costs of all other alternatives for arriving at the expected utility of one alternative and that they disregard costs directly connected with the alternative under consideration (see above). Second, when more than two alternatives are involved, the models differ with regard to the amount of information used by individuals. The sequential discrimination model assumes that choice probabilities are established on the basis of a pairwise comparison of alternatives, while the CB model implies that individuals make use of the entire reward schedule for arriving at a single choice probability.

In choice situations with more than two alternatives and with negative elementary

[5] For the Ofshe experiments, I could not detect any difference in instructions. However, the experiments reported in Table 2 were done later and with fewer subjects than the experiments reported in Table 4. Maybe the instruction session was more routinized and less enthusiastic for the later experiments.

Table 5. Summary of the Three-Alternative Experiments by Siegal et al.

Experiment	π_1	π_2	π_3	r_{11}	r_{12} r_{13}	r_{22} r_{33}	other r	P_1	P_2	P_3	a[a]	$1/\Sigma G_j$	$a\Sigma G_j$
W	.65	.25	.10	5	−5	1	−1	.785	.119	.096	.2478	.0962	2.577
X	.75	.20	.05	5	−5	1	−1	.891	.076	.033	.2574	.1	2.574
Y	.70	.15	.15	5	−5	1	−1	.876	.058	.066	.2785	.0980	2.841
Z[b]	.70	.50	.40	5	−5	1	−1	.814	.120	.066	.2854	.0725	3.938

[a] The marginal utilities are calculated for the sequential and not the simultaneous model (see Table 6).
[b] In this experiment the π's do not add up to unity. They overlap such that $g_1 = 5(.7-.2-.1) = 2$; $g_2 = .5-.4-.1 = 0$; $g_3 = .4-.4-.2 = -.2$ (see Siegel et al., 1964:123).

outcomes, assumptions on both organization and amount of information become relevant. Siegel et al. (1964:117ff.) provided us with four experiments that meet these conditions. They are summarized in Table 5 and can be used to compare the predictive accuracy of both models and, indirectly, the strength of the cognitive assumptions. In all cases, the conditions for the sequential model are satisfied.

Since the discrimination model has one open parameter (a), one of the four experiments has to be used to estimate a. Which one? It was decided to use each experiment once to establish $\hat{a}$ in order to predict the other three. In this way, the range of predictive accuracy can be shown in four sets of predictions. The left part of Table 6 ("Sequential Model") shows the results. The average absolute discrepancies ($\bar{d}$) and their standard deviations (s) are quite acceptable on intuitive grounds. When these results are compared to the predictions of the CB model (right side of Table 6), the difference is striking ($\bar{d}$=.281 and s=.11). These predictions are virtually worthless.

Is this poor performance of the CB model due to one or the other cognitive assumption? In order to help answer this question, the predictions from the simultaneous discrimination model are also presented in Table 6. This version of the model differs from the sequential model only with regard to the cognitive assumption on amount of information. It implies that the individual considers the entire reward schedule for making a single choice, rather than using pairwise comparisons. While the results are worse than those of the sequential model, they are still far superior to the results derived from the CB model. Thus, the cognitive assumption on amount of information of the CB model cannot be the main reason for its poor performance.

As can be seen from the right side of Table 6, the CB model predictions are worst for P_1 (the largest P). In fact, P_1 is systematically underestimated by a large amount, and therefore the two smaller P's are systematically overestimated. Why is this so? Due to the CB model's assumption on organization of information, the relatively heavy costs in alternative (1), viz. $-5\pi_2$ and $-5\pi_3$, are accredited as benefits to alternatives (2) and (3), greatly inflating their expected utility and deflating the expected utility of alternative (1). Since P_1 is predicted on the basis of its relative weight in terms of expected utility, it comes out much too small. The cognitive assumption on organization of information implied by the CB model seems to be untenable, at least in this test. This conclusion is strengthened by a look at

Table 6. Average Absolute Discrepancy ($\bar{d}$) and Its Standard Deviation (s) for the Experiments of Table 5 Using the Discrimination Model in Two Versions. On the Right, the Absolute Discrepancies for the CB Model

		Sequential Model		Simultaneous Model		CB Model	
$\hat{a}$ based on		$\bar{d}$	s	$\bar{d}$	s	d for P_1	d for P_2
Experiment	W	.031	.008	.040	.030	.314	.160
	X	.036	.018	.068	.030	.341	.164
	Y	.024	.026	.045	.032	.366	.187
	Z	.026	.031	.049	.034	.492	.224

Tables 2–4. The average absolute discrepancy for CB-predictions that do not involve this cognitive assumption is .079, while the average absolute discrepancy for CB-predictions that do involve this assumption (experiments 5–7 in Table 4) is .148. Yet, this assumption cannot be dropped without making the model inapplicable to all cases where expected utility is negative. Even if one was willing to pay this heavy price, however, one would still be left with a model that cannot cope with changes in marginal utility, as we saw above.

While expected positive utility seems to lead to untenable cognitive assumptions (and predictions), it still may have its use in providing an anchor for the evaluation of a. The ratio of a to $1/\Sigma G_j$ varies between 2.57 and 3.94 for the three-alternative experiments (see Table 5). If $1/\Sigma G_j$ really is an anchor for a, there should be a reason why $a\Sigma G_j$ is so much higher for these experiments than for the two-alternative experiments presented above. The solution may lie in Siegel's hypothesis that a three-alternative choice situation is less boring than a two-alternative one (see Siegel et al., 1964:80). A reduction in boredom reduces the weight of the disutility of discrimination; and since a measures the weight of the utility of discrimination relative to the disutility of discrimination, a reduction in the latter will result in an increase of a. This explanation strengthens the guess that $1/\Sigma G_j$ is an anchor for a.

HEURISTIC ASPECTS OF THE MODELS

An important feature of any decision-making model is its ability to direct the search for relevant factors in the choice situation and to guide the production of estimates when relevant information is lacking. For example, the explicit inclusion of a marginal utility factor in the discrimination model directs attention to aspects that influence the marginal utility, such as the wording of instructions, variations in boredom, equity considerations, etc. This section will concentrate on two heuristic aspects: the search for relevant utility arguments, and the estimation of subjective probabilities.

Utility Arguments

The disutility of discrimination (see equation 4 above) is based on the idea that it is better to work with a global utility term than with lists of utility arguments when building a model for aggregate data, because individuals are likely to have an idiosyncratic scatter of "motives" for deviating from the pure strategy. The marginal utility parameter a similarly encourages a global utility term for discrimination because it applies to the weight of the good or entire basket of goods that motivates towards discrimination of alternatives relative to the weight of the basket of goods that motivates towards nondiscrimination. In short, the discrimination model clearly discourages lists of utility arguments.

When decision-making models are applied to homogeneous goods (such as money), this heuristic aspect does not matter much. But sociologists have long learned to look for various nonmonetary rewards and punishments in social situations, such as social approval, ego involvement, self-esteem, norm conformity, etc. When decision-making models are applied in sociology, it seems only natural to make use of these sociological insights and to translate them into lists of utility arguments. It will seem natural, that is, unless the model explicitly discourages these lists. The CB model lends itself to the list approach because it is not tied to any heuristic assumption that would discourage such lists. Which model provides a better guide for the application in social situations? This question will be taken up shortly as part of an analysis of two examples. Before that, we will briefly turn to subjective event probabilities.

Subjective Event Probabilities

Subjective event probabilities are a core element of both models. Without them, the models cannot be applied. In the Siegel and the Ofshe experiments, objective event probabilities were not known to the subjects beforehand but were learned in the process. The researchers, however, knew these probabilities and could use them as estimates for subjective probabilities *because* subjects learned. In more complex situations, objective event probabilities may not be known or may not even exist in any sense relevant to the decision-making. What can we do then? There are various ways to estimate them. For example, they can be estimated by assigning numbers to verbal statements such as "sure" and "not sure." Or they can be established ad hoc by some plausible assumption. Sometimes, they can be inferred by shifting the estimating procedure to all other elements of the model and then using the model to calculate the subjective probabilities. At times, any one of these methods may be unavoidable, but none of them is tied to the heuristics of the model itself or to any theory on subjective probabilities.

The discrimination model suggests a particular experimental setup for estimating subjective event probabilities that avoids shifting the burden to other elements and avoids the arbitrariness of ad hoc assumptions and quantified verbal statements. This setup is one in which the model predicts matching of choice and subjective event probabilities. The observed choice probabilities can then be used as estimates for the subjective event probabilities. Thus, one should create or find a choice situation in which the event probabilities can be expected to be similar or identical to the situation under study, and in which there are no extra tangible or intangible costs or benefits.

In order to exemplify this procedure and the heuristics of global utility components, two experiments of the Berger-Camilleri program (Camilleri et al., 1972, and Camilleri and Conner, 1976), which have been presented with the CB model by the authors, will be analyzed. In the process, some seemingly technical details of the CB estimating procedure must be presented in order to show the importance of the heuristic aspects mentioned.

EXAMPLE I

The basic experimental situation was described as follows:

> A pair of subjects is asked to make binary choices in two steps. The subjects are shown slides presenting two alternatives. They are given the instruction to make a provisional, independent decision between the alternatives; then, after being told what the other has decided, each is to take this information into account as he sees fit in making a final decision on the trial. A subject's final choices are not communicated to his partner. Subjects are led to believe that final decisions are being evaluated as "correct" or "incorrect" and that such evaluations constitute their performance score in the task situation. These evaluations, however, are not communicated by the experimenter to the subjects during the series of trials. (Camilleri et al., 1972:30)

In these situations, the information exchange was manipulated in such a way that the experimenter created continuous or almost continuous disagreement between the subjects on their provisional choices. The crucial question is whether a subject changed his response in view of the apparent disagreement ("other response") or whether he stuck to his original response ("self response"). The choices were made under various structural conditions. Each subject was induced to believe that he had either superior or below average ability for making the correct choice, and he was informed about the (apparent) ability (superior or below average) of his partner. This created "expectation states": high ability for self and low for other [+−]; high/high [++]; low/low [−−]; and low/high [−+].

In addition, conditions differed with regard to control: the team performance was either attributed to self (on the basis of his final choice, regardless of what the partner's final choice was), called condition of *Full-control*; or it was attributed to other, called condition of *No-control*; or the final choices were weighted equally in determining the team's performance, called condition of *Equal-control*. The results are shown in Table 7.

Application of the CB Model

Utility assumptions and estimating procedures. In order to apply the CB model to this experiment, the authors made various utility assumptions through a listing approach of rewards they thought operative in the experimental situation:

Table 7. Predicted and Observed Choice Frequencies for "Self Response" in the Experiment, as Reported by Camilleri and Conner (1976:34)

Expectation State	Full-control		Equal-control		No-control	
	Pred.	Obs.	Pred.	Obs.	Pred.	Obs.
[+−]	.75	.73	.77	.78	.80	.82
[++]	X	.60	X	.67	X	.71
[−−]	.60	.52	.67	.65	.71	.73
[−+]	.47	.24	.55	.44	.60	.43

u_1: the utility of being consistent (for all conditions);
u_2: the utility of approval of partner for correct final choice in Full-control condition and No-control condition;
u_3: the utility of approval for correct final choice by experimenter (for all conditions).

In addition to these utilities, the subjective probability (π) of being correct in the final choice had to be estimated. In effect, the authors attempted to translate the expectation states into subjective probabilities on the basis of the experimental manipulation. For the low/low [−−] and high/high [++] conditions, subjects were told they had as many correct choices as the partner, hence $\hat{\pi}$ = .50. In the high/low [+−] condition, subjects were told that they got approximately twice as many correct choices as the other, so that $\hat{\pi} = 2/3$, and for [−+], $\hat{\pi} = 1/3$, accordingly.

Predictions and discussion. On the basis of the utility and probability assumptions and the model itself, the authors arrived at the following basic prediction equation, where P_s = probability of a consistent final choice (or "self response"):

$$P_s = \frac{u_1 + \pi\,(u_2 + u_3)}{u_1 + u_2 + u_3} \qquad (21)$$

This equation was adapted for the different conditions (for instance, for the case where $u_2 = 0$) and with the help of one observed choice proportion per control condition, the authors could compute the predictions shown in Table 7. The average absolute discrepancy between observed and predicted choice probabilities is .076 (with s=.075). This result is not very satisfying. Note that the estimating procedure for the subjective probabilities is completely ad hoc, because it disregards the authors' own manipulation. For example, during the creation of expectation states, "high" subjects [+] were told that 17 out of their 20 decisions were "correct," *and* they were instructed that this constituted a "superior" ability. Assuming that the subjects believed the evaluator and considering that individuals are generally quite willing to accept a positive evaluation of themselves, they should have felt very confident regarding the task at hand. Contrary to this manipulation effect, Camilleri and Berger assumed that being confronted with another (disagreeing) "expert," the confidence level was immediately reduced to .5 (no better than chance). Why? The reasoning is ad hoc. The same is true for "low" subjects [−]. They were told that eight of their 20 decisions were "correct" (indicating "below average ability"). Assuming that the subjects believed the evaluator and considering that individuals are generally reluctant to accept a negative evaluation of themselves,[6] their confidence level should certainly be higher than .4. Yet, Camilleri and Berger assumed that it immediately dropped to .33 when the subjects were confronted with a disagreeing "expert." Why?

The listing approach seems reasonable

[6] Replicating some parts of this experiment with one and with two evaluators, Webster et al. (1972:594) seem to have found evidence contradicting this basic theorem of balance and attribution theory. However, their analysis confounds the expectation state manipulation with the effect of a disagreeing partner. Their conclusion is thus questionable

enough. After all, we know from sociological and social psychological research that approval is a reward for most people and that being consistent is at least a norm frequently encountered. But there are many nagging problems. Why only those three utility arguments? We know that most people consider "being right" also a reward—why not add it to the list? We also know that most people consider disagreement unpleasant and agreement pleasant—why not add agreement as an additional utility argument? The answer is quickly found. Since these subtle costs and benefits are all difficult to measure, and since even if they could be measured it would be difficult to find a common measure for them all, they are left as theoretical constructs and are indirectly assessed with the help of the observed choice frequencies. This limits the number of utility arguments that can be considered. If more than three had been used by the authors, they could not have arrived at numerical utility ratios. Thus, the list is arbitrarily limited by the estimating procedure. What then should be included in the list and what should not, if only three arguments can be chosen? This is a very arbitrary decision, and we will see in Example II that without a hint at the arbitrariness, the authors made a different selection of utility arguments.

There are many more arbitrary decisions evoked by the listing approach. The authors established a particular hypothetical reward schedule with the utility arguments (see Table 8). In this schedule, they assumed that the lack of approval is costly. Why? In addition, they assumed that the absolute value of this cost is equal to the value of the reward individuals get from approval. Why? Is lack of approval equal to disapproval, and if this is so, is disapproval just as punishing as approval is rewarding? They also assumed that being inconsistent is just as punishing as being consistent is rewarding.

Table 8. Reward Schedule Assumed in Expectation State Experiment

	Probability of being right if Stay π	Probability of being right if Change $1-\pi$
Stay	u_1, u_2, u_3	$u_1, -u_2, -u_3$
Change	$-u_1, -u_2, -u_3$	$u_2, u_3, -u_1$

The estimating procedure for utility ratios is responsible for some of these assumptions. For example, negative utility ratios are meaningless in this theory and must be avoided. This commits the authors to $\pi \leq P_s$, a condition which is violated only once in the [−+] Full-control condition. Had they dropped the assumption that inconsistency is punishing, they would have committed themselves to $2\pi \leq P_s$, violated by all conditions. This means they cannot drop the assumption even if they are convinced that it is wrong. The estimating procedure also makes them assume that u_1/u_3 and $u_1/(u_2+u_3)$ are constant for all expectation states. If they do not assume this, they cannot use estimates from one state for predictions in another. Yet this assumption is quite absurd. It implies that the prouder a subject is of a consistent response, the less he values approval for his deed.

In short, the listing approach is especially unattractive when utility arguments cannot be measured commensurably. Then, the *technical* aspects of the estimating procedures decide most of the *substantive* assumptions. And due to the listing approach, there are many such assumptions needed.

Application of the Discrimination Model

Utility assumptions and estimating procedures. There were no monetary rewards involved in the experiment. But what is the source of the nonmonetary rewards? The experimenters created two "roles": the Decision-maker (Full-control condition) and the Advisor (No-control condition). Special nonmonetary rewards must be connected to these roles. In the Equal-control condition, there are no such roles and it is therefore fair to assume that the Equal-control condition does not differ from other experimental arrangements in which there is just the possibility of being right or being wrong. The discrimination model predicts matching for these kinds of circumstances (see above). Thus, the choice probabilities for the Equal-control condition can be interpreted as the subjective probabilities of being right when staying (for the various conditions and expectation states). The heuristics of the discrimination model thus provide us with theoretically founded estimates for π (see Table 7 above).

What, then, are the nonmonetary costs and benefits connected with the two roles? As was said earlier, the discrimination model discourages lists of utility arguments. We are thus looking for baskets of costs and rewards. This means that we are looking for some factor on which other utility arguments (such as approval, being right, etc.) depend. The central idea for such a basket is the following. All costs and benefits in the situation are mediated by the expectation state. For example, if the subject is right when staying, then self-approval for doing so is proportional to the subjective probability of being right when staying. The same holds for being right when changing. In other words, the nonexpert derives a larger reward from changing his or her opinion toward the judgment of the partner than from staying, and vice-versa for the expert. Thus, approval by the experimenter is also not the same for expert and nonexpert. If you tell somebody that his judgment ability is below average, then it is very likely that this somebody expects more approval from you when he does not insist on his judgment. The reverse is true for the expert. In short, the basic factor (and measure) for the rewards when being right is π for staying and $1-\pi$ for changing.

Advisors' judgments do not count for the team. Therefore it is assumed that Advisors do not feel punished when their judgment is wrong. For *Decision-makers* the situation is different because their judgment does count for the team. What punishment is there when they stay (i.e., do not listen to the Advisor) and are wrong? It is fair to assume that they will be blamed (by self and others) the more, the more they were supposed to be expert. Thus, the cost for being wrong when staying is $-\pi$. What is the punishment for changing (i.e., listening to the Advisor) and being wrong? In this situation, there is a positive and a negative aspect. Positive is being right on the first guess (reward π), and negative is that the final judgment was wrong (cost $-\pi$). Thus, the reward and the cost cancel out for the combination change/wrong.

The resulting reward schedule is shown in Table 9. The difference with the CB procedure (resulting in schedule Table 8) is not that assumptions had to be made in the latter and not in the former. Of course, assumptions are necessary; but the kinds of assumptions made for the discrimination model are (a) guided by the search for a global utility argument on which other utility aspects of the situation depend, and (b) made on the basis of substantive considerations rather than forced by technical aspects of the estimating procedure. Thus, the reward schedule in Table 9 is preferable to the reward schedule in Table 8 on these grounds alone. But does it lead to better predictions?

Predictions. The necessary estimate for the marginal utility should be made from the highest (g_s-g_c). This is the case for $P_s = .82$ in the No-control condition, with $\hat{a} = 1.14287$. Now all the information necessary for predictions is at hand. For example, for the "Full-control" condition and the $[+-]$ expectation state, $\hat{\pi}_s = .78$ (see Table 7), $g_s-g_c = \hat{\pi}_s^2+\hat{\pi}_s-1 = .3884$ and thus $P_s = \frac{1.14287}{2}(.3884) + .5 = .722$. The summary of the predictions is given in Table 10 in terms of absolute discrepancies from the observed probabilities. Compared to the predictions from

Table 9. Reward Schedule for Expectation State Experiment Assumed with the Discrimination Model

	Advisor		Decision-maker	
	Probability: right when Stay π	Probability: right when Change $1-\pi$	Probability: right when Stay π	Probability: right when Change $1-\pi$
Stay	π	0	π	$-\pi$
Change	0	$1-\pi$	0	$1-\pi$

Table 10. Absolute Discrepancies (d) for Predictions by Discrimination Model

Expectation state	$\hat{\pi}$	Decision-maker (d)	Advisor (d)
[+−]	.78	.008	X
[++]	.67	.032	.016
[−−]	.65	.021	.059
[−+]	.44	.051	.001

the CB model for these two conditions (see Table 7), the discrimination model does very well: the former produced an average absolute discrepancy of $\bar{d}$=.09 (with s=.082), while the latter produced $\bar{d}$=.027 (with s=.020).

Some additional confidence in these results can be derived from an experiment by Balkwell (1969). He replicated the Camilleri-Berger experiment with one important difference: instead of "full" and "no" control, he had "⅔ control" and "⅓ control" as experimental conditions. If our reward schedules in Table 9 are correct, then Balkwell's conditions must be expressed as "$-⅔\,\pi$" and "$-⅓\,\pi$" replacing "$-\pi$" and "0" respectively in the northeast corners. The result is encouraging:[7] with $\hat{a}$=1.19 estimated from Balkwell's Low Power [+−] condition (where g_1-g_2 is highest), $\bar{d}$=.022 and s=.016.

Comparison

While the discrimination model did much better than the CB model with these data, it is not certain whether the difference lies mainly in the models themselves or mainly in their heuristic capabilities regarding π estimates and utility assumptions. For an answer to this question, the following calculations[8] were carried out: (i) the π estimates and the reward schedule from the discrimination model were used with the CB model; (ii) the π estimates from the CB model were used in the discrimination model. The results of these computations in terms of average absolute discrepancies and their standard deviations are for (i): $\bar{d}$ = .046 and s = .030; for (ii): $\bar{d}$ = .236 and s = .60. As can be seen from test condition (i), the CB predictions are much improved by the utility assumptions and π estimates from the discrimination model (compare this to $\bar{d}$ = .09 and s = .082). Thus, a large part of the problem with the CB predictions lies in the utility lists and ad hoc π estimates. The latter point is underlined by the very poor results of test condition (ii) in which the CB estimates for π were used in the discrimination model. Yet, even the greatly improved results in test condition (i) are considerably worse than the results produced by the discrimination model with its own estimates ($\bar{d}$ = .027 and s = .020), so that the CB model also contributes considerably to the prediction difficulties. Is this performance by the discrimination model and its heuristics a lucky hit, or can it be reproduced with other data? This question will be dealt with in Example II.

[7] With an ingenious but very elaborate estimating procedure using many ad hoc assumptions and all of the data from the CB experiment, Balkwell is able to achieve $\bar{d}$=.035 and s=.020. Using yet another, less complicated procedure on these data, Kervin (1974) comes to the same result. But Kervin's procedure is no improvement. Applied to the CB data, it yields $\bar{d}$=.054 and s=.048, which is better than the CB predictions but still not encouraging.

[8] It was not possible to use only the π estimates of the discrimination model for the CB model, because the CB utility assumptions limit π to $\pi \leq P_s$. It was also not possible to use the CB utilities in the discrimination model because they have no numerical values.

EXAMPLE II

The experimental setup described in Example I was extended by Camilleri and Conner (1976) to include another disagreeing partner, thereby creating ternary expectation states. Conditions were otherwise identical, with the exception that no Equal-control condition was run. The surprising result was that the observed choice probabilities (shown in Table 11) differed *greatly* from those in

Table 11. Observed Choice Probabilities (for Staying) in Experiment by Camilleri and Conner (1976) with Ternary Expectation States. Observed Choice Probabilities for the Binary Expectation States (see Table 7) are Given in Parentheses

Expectation state	Full-control (Decision-maker)	No-control (Advisor)
[+ − −]	.63 (.73)	.79 (.82)
[+ + +]	.25 (.60)	.40 (.71)
[− − −]	.30 (.52)	.59 (.73)
[− + +]	.02 (.24)	.11 (.43)

the experiment with only one disagreeing partner. How could this be explained?

Application of the CB Model

Utility assumptions and estimating procedures. Camilleri and Conner first applied the same utility assumptions and π estimates as in Example I. With the help of two observed P's from the ternary experiment and the prior assumptions, they could produce predictions for the ternary experiment. The results ($\bar{d}$ = .122 and s = .060) did not satisfy them. In order to improve matters, they discarded the idea of prediction (or rather postdiction) in favor of a more modest goal: to see whether the model could be made to fit the data in such a way that π's and utility ratios take on theoretically possible or even meaningful values.

As a first step, they suggested a new procedure for arriving at π estimates through these ad hoc assumptions: that u_1/u_3 is constant for all conditions; that the value of π and the value of u_3 are unaffected by whether the subject is an Advisor or a Decision-maker; and that π for [+ −] is equal to $1-\pi$ for [− +] in the Advisor (or No-control) condition. These assumptions were not defended and had the purpose of allowing the calculation of π's and utility ratios on the basis of the observed p's. The resulting π's shown in Table 12 (as Estimate 1) are not all positive and the u_2/u_3 ratios are almost all negative. This is theoretically unacceptable.

In order to arrive at acceptable π estimates and utility ratios, they changed the utility assumptions such that u_1 and u_2 were replaced by u_4 and u_5, respectively (u_3 remained unchanged):

u_4: the utility of being consistent *and* correct;

u_5: the utility of the partner's positive evaluation of a change-response (and the disutility of his negative evaluation of a stay response), i.e., the utility of agreement and disutility of disagreement with the partner.

Table 12. Various Sets of π Estimates by Camilleri and Conner (1976)

Expectation state	Estimate 1	Estimate 2	Estimate 3	Estimate 4
[+ − −]	.72	.67	.57	.67
[+ + +]	.20	.26	.35	.25
[− − −]	.45	.44	.35	.45
[− + +]	−.19	.06	.19	.12

Why had these utilities not been considered before and why do they replace the old ones rather than complement them? The answer has been provided before: no prediction is possible if, given the experimental conditions, more than three utility arguments are used.

The new prediction equations are:

$$P_s = \frac{\pi\,(u_4/u_3) + 2\pi}{\pi\,(u_4/u_3) + 2} \quad \text{for Advisor (No-control)} \quad (22)$$

$$P_s = \frac{\pi\,(u_4/u_3) + 2\pi}{\pi\,(u_4/u_5) + 2\,(u_5/u_3) + 2} \quad \text{for Decision-maker (Full-control)} \quad (23)$$

With these equations, three ad hoc assumptions[9] and the observed P's, a new series of π estimates and utility ratios was produced (see Table 12, Estimate 2). This time, the π estimates and u_5/u_3 ratios came out positive.[10] Changing the utility list made it possible to fit the model to the data. The next, more ambitious question was: is it possible to arrive at the π estimates without using the observed P's?

In order to answer this question, the authors returned to their original procedure of estimating π on the basis of the expectation state manipulation, with $\pi = P_s/(p_s+p_o)$, where p_s=proportion of right answers by ego and p_o=proportion of right answers by other(s). The results are shown in Table 12 as Estimate 3. Unfortunately, they did not lead to a good fit.

A last attempt was made to arrive at satisfactory π estimates. It was similarly

[9] These assumptions are: u_4/u_3 and u_3 are constant across conditions and $\pi_{[+-]} = 1-\pi_{[-+]}$.

[10] The π estimates correlate almost perfectly with the observed P's, as they should. The correlation between P's and utility ratios is negative and almost as high. If u_3 is indeed constant, as the authors assume, then u_5 strongly correlates with the change-response $(1-P_s)$, which is also as it should be: the reward schedule is set up in such a way that every change-response is rewarded with $2u_5$, independent of event probabilities.

based on the expectation state procedure but differed from the previous attempt in two regards: conditional probabilities were used, and the p_s and p_o proportions were selected not from the experimental procedure but so as to maximize the fit. The formula was: $\pi = p_s(1-p_o)^2/[p_s(1-p_o)^2+(1-p_s)p_o^2]$. The best-fitting proportions ($p_s = .75$ for "high" subjects and $p_s = .55$ for "low" subjects) differed considerably from the true ones (.85 and .4, respectively). The result is shown in Table 12, Estimate 4.

We have come full circle back to the original idea that π must be a function of the number of right answers in the manipulation phase. The whole exercise failed to produce a new idea about the estimation of π. The new utility list seems to be an improvement, but even this did not render the model predictive. Quite obviously, the authors were not really satisfied with any of these solutions, and their suggestion at the end of the paper is symptomatic for the listing approach. They state that "an even more complicated version of the model with *additional utilities* and interactions between utilities may eventually be needed" (Camilleri and Conner, 1976:38; emphasis added).

Application of the Discrimination Model

Utility assumptions and estimating procedures. There is no reason to change the reward schedule assumed for Example I (see Table 9), because the experimental setup in the ternary experiment is unchanged as far as costs and benefits are concerned. What has to be changed are the π's since being confronted with two disagreeing partners must have an influence on the subject's probability of being right (viz. lower it). Unfortunately, Camilleri and Conner did not run the Equal-control condition so that there is no *direct* basis for estimating the π's by the matching assumption. Instead, a detour has to be taken.

The estimating procedure is based on the following idea. We assume on the grounds of standard social psychological insights that disagreeing partners progressively reduce ego's confidence the more "expert" the partners are thought to be. At the same time, we are directed by the heuristics of the discrimination model to link this assumption to the estimates already derived from "matching," because the model established the latter as theoretically sound estimates. The link is made in the following way. As said earlier, the confidence level for "high" subjects must have been very high. They had been told that 17 of their 20 answers were "correct" *and* that they were "superior." Let us assume, somewhat arbitrarily, that the original $\pi_s = .95$ for [+]. We observe that with an "inferior" [−] disagreeing partner added, confidence drops to $\pi_s=.78$, our estimate from the binary case. This is a reduction of roughly 18%. Similarly, we observe that with the addition of a "superior" [+] partner, confidence drops to $\pi_s=.67$, or roughly by 30%. On this basis, we assume that the addition of a second inferior disagreeing partner will reduce confidence again by 18%, and that addition of a second superior partner will reduce confidence again by 30%. Since we have good reason to assume the original superior confidence level to be somewhere between .9 and unity, but no good reason for estimating the original inferior confidence level, we assume that the reductions of 18% and 30% apply similarly to subjects with inferior expectation states. In this way, we arrive at the π estimates shown in Table 13, which should be compared to the set of estimates by Camilleri and Conner (Table 12).

Predictions. For the estimate of the marginal utility, we use again the observed P_s with the highest g_s-g_c, viz. $P_s=.79$ for the Advisor (No-control) and [+−−] condition: $\hat{a} = 2.07143$. The reward schedule is as in Table 9 above. By use of the prediction equation 7, the new

Table 13. π Estimates Connected with the Discrimination Model for the Camilleri-Conner (1976) Experiment

Expectation state	Binary π est.	Reduction	Ternary π est.
[+ − −]	.78	18%	.64
[+ + +]	.67	30%	.47
[− − −]	.65	18%	.53
[− + +]	.44	30%	.31

predictions are derived and shown in Table 14 in terms of absolute discrepancies.

The discrimination model does very well with these data. But how arbitrary is the assumed original confidence level of .95? Table 15 shows the average absolute discrepancies and standard deviations for various confidence levels. We see that a confidence level of .94 would have been slightly better, but none of the results are obviously intolerable. In a similar situation in the future, one might compute the confidence level that gives the best fit rather than to set a (be it plausible) level a priori.

Comparison

Again the question arises whether the trouble with the CB model with regard to these data lay mainly with the model itself or mainly with the estimates and utility list accompanying the model. In order to answer this question, the π estimates and reward assumptions from the discrimination model were used to produce predictions from the CB model. The result is again a big improvement for the CB model: $\bar{d} = .05$ and $s = .025$ (compare this to the original predictions with $\bar{d} = .122$ and $s = .060$). These results are still inferior to those of the discrimination model, but they show that one major problem with the CB model is that it does not guide estimating procedures and utility assumptions in the right direction: it has no marginal utility concept that could help estimate the π's (for instance, through prediction of matching) and it does not encourage global utility arguments or discourage lists of rewards. How important the heuristic aspects of a model are may have been sufficiently illustrated by these two examples.

Table 14. Absolute Discrepancies (d) for Predictions by Discrimination Model

Expectation state	Full-control (d) (Decision-maker)	No-control (d) (Advisor)
[+ − −]	.08	X
[+ + +]	.07	.04
[− − −]	.00	.03
[− + +]	.02	.00

Table 15. Average Absolute Discrepancies (d) and Their Standard Deviation (s) for Various Confidence Levels (See Text)

	Original Confidence Level					
	.92	.93	.94	.95	.96	.97
$\bar{d}$	.040	.037	.034	.034	.043	.056
s	.032	.022	.019	.029	.031	.040

SUMMARY AND CONCLUSION

Most sociologists are interested in recurrent social behavior. For this reason, a decision-making model should be able to explain choice frequencies for repetitive choice situations. But this is not easily done. First, there is the well-documented sociological insight that individuals are not generally gain-maximizers. Second, there is the problem of applying quantitative models to social situations: rewards and costs are subtle and difficult to measure commensurably, and subjective probabilities are often not known.

A decision-making model relevant for a broad range of sociological problems must confront these issues. Both models compared in this paper deal with repetitive choice, but only the discrimination model explains restraints on gain maximization and possesses the heuristic capabilities to guide its application to social situations. The Camilleri-Berger model does not consider marginal utility and *therefore* has no way of expressing the relative (and changing) weight of factors that restrain the individual from choosing the pure strategy (gain-maximizing). And lacking a measure for the relative weight of two opposite utility components, the CB model is conducive to the listing approach in which utility arguments are items on a list of motives. Since these motives cannot easily be measured in a commensurable way, they have to be estimated from the observed data. This reduces the explanatory power of the model, and, even worse, it forces the theorist to let technical aspects of the estimating procedure dominate the selection of utility assumptions.

The detailed comparison between the two models showed in particular that the CB model contains a number of untenable implications: that marginal utility depends solely on the reward schedule; that matching between choice and event probabilities occurs whenever the ratio of expected positive utilities equals the ratio of event probabilities; that the cognitive organization of information is such that benefits of one alternative are increased by the costs of other alternatives.

None of these implications are contained in the discrimination model. And, from the point of view of philosophy of science, the discrimination model has an important additional advantage. It can specify the circumstances under which the CB model does provide accurate predictions: the closer the true marginal utility is to the inverse of the sum of expected positive utilities, the more accurate the CB predictions.[11] In this sense, it can be said that the discrimination model is a "deeper" theory (cf. Popper, 1972:16, 196 ff.) than the Camilleri-Berger model.

[11] In all likelihood, this approximation occurs only when the individual is disinterested in the choice situation but not quite willing to pay the costs of avoiding it.

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ERRATUM

The article by Siegwart Lindenberg, "Rational Repetitive Choice: The Discrimination Model versus the Camilleri-Berger Model," which appeared in the December, 1981 issue of SPQ, contained the following error: page 319, left column, the proof should read:

$$P_i = \frac{a}{k}(kg_i - \sum_{j=1}^{k} g_j) + \frac{1}{k} \qquad (10)$$

$$g_i = \pi_i; \sum_{j=1}^{k} g_j = \sum_{j=1}^{k} \pi_j = 1; a = 1;$$

$$P_i = \frac{1}{k}(k\pi_i - 1) + \frac{1}{k} = \pi_i. \quad \text{Q.E.D.}$$

The last two lines of this proof appeared by mistake on p. 323 in front of equation 21. They should be deleted on that page.