CHOICE, CHANGEOVER, AND TRAVEL: A QUANTITATIVE MODEL

Michael Davison

UNIVERSITY OF AUCKLAND

Six pigeons were trained on concurrent variable-interval schedules in which responding on fixed-interval schedules was required to give access to the alternate schedule. Responding on the concurrent schedules was not allowed, after changing over had commenced, until the changeover schedule had been completed. In Parts 1 to 3 of the experiment, the changeover fixed-interval schedules were equal and were 0 s, 10 s, and 20 s, respectively. In each part, the relative frequency of reinforcement obtained on the concurrent schedules was varied over at least five conditions. In Part 4, the concurrent schedules were equal, and one changeover fixed-interval schedule was twice the other. Under these conditions, the absolute sizes of the changeover schedules were varied. Increasing the changeover requirement from 0 s to 10 s (Parts 1 and 2) resulted in increases in the sensitivity of behavior allocation to reinforcers obtained, but no further increase was obtained when the changeover schedules were increased to 20 s (Part 3). In Part 4, performance was biased towards the concurrent schedule that took less time to enter. These results are consistent with a subtractive punishment model of travel in which the degree of punishment is measured by the number of reinforcers apparently lost from a schedule when the subject changes to that schedule. Absolute times spent on the main keys could be accurately described by a previous model of changeover performance.

Key words: choice, changeovers, concurrent schedules, overmatching, punishment model, pecking, pigeons

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Baum (1982) argued that one of the many major differences between foraging in natural environments and its much simplified laboratory analogue, performing on concurrent variable-interval (VI) schedules, is the distance that separates the patches. In nature, the existence of functionally separate patches only 20 cm apart is, for pigeons, obviously very rare or simple impossible. Baum, therefore, investigated the effect of travel between the concurrent VI VI patches in a laboratory setting to see how this variable affected the way in which pigeons distributed their responses and time between the patches. He directly varied the distance between the pecking keys by requiring the subjects to negotiate a partition, with an additional hurdle in some conditions, to change between the schedules. Preference became more extreme as changeover requirements were (ordinally) increased, and both response and time ratios reliably exceeded obtained reinforcer ratios at the greater requirements.

Similar data were obtained by Pliskoff, Cicerone, and Nelson (1978). They required pigeons to respond on fixed-ratio (FR) schedules to change between various concurrent VI VI schedules providing 0.67 reinforcers per minute. In this experiment, the VI schedules stopped timing between the initiation and completion of a changeover (Baum, 1982, did not mention this aspect of his procedure). FR 5 schedules were used in one experiment and FR 10 in the other. Unfortunately, different subjects were used in the two experiments. According to Baum's (1982) reanalysis of Pliskoff et al.'s data, response distributions were more extreme than reinforcer distributions for both FR schedules, and time ratios were more extreme than reinforcer ratios for the FR 10 changeover requirement.

Radically different results were obtained by Tustin and Davison (1979), as shown in the reanalysis of their data reported by Davison and McCarthy (1988). In the experiment reported by Davison and McCarthy, Tustin and Davison required subjects to complete VI

schedules varying from 15 s to 360 s in order to change over between concurrent VI VI schedules. As changeover-schedule times were increased, both response and time distributions became less extreme than reinforcer distributions, but changeover-key response distributions increased to close to obtained reinforcer distributions. The procedure used by Tustin and Davison was, however, quite different from that used by Baum (1982) and by Pliskoff et al. (1978). In Tustin and Davison's experiment, the changeover schedules were available concurrently with the main-key schedules, so that the subjects were allowed to continue foraging while traveling. Species will, of course, differ as to whether reinforcers are obtained while traveling between patches.

Baum (1982) entertained a quantitative model for his data. When changeovers are directly punished or have a cost, response ratios exceed reinforcer ratios (Todorov, 1971) in much the same way as they do when travel requirements are increased. Changing over, or travel, may be readily interpreted as a punisher, and hence quantitative punishment models of the type suggested by de Villiers (1980), Farley (1980), and Farley and Fantino (1978) might account for Baum's data. When using equal response-based changeover requirements, the overall amount of work done in changing over is proportional to the overall frequency of changing over, so Baum suggested Equation 1:

$$\frac{B_r}{B_g} = c\left(\frac{R_r - qC_{rg}}{R_g - qC_{gr}}\right), \qquad (1)$$

where B refers to responses, R to reinforcers obtained, and C to the overall rate of changeovers between the keys. The subscripts r (red) and g (green) denote the two concurrent alternatives, c is bias between the keys (Baum, 1974), and q measures the cost of changing over. Baum reported, however, that this model provided a poor account of his data and those of Pliskoff et al. (1978) and Todorov (1971). (Baum also raised the right-hand side of Equation 1 to a power a, but in his fits attempted to produce a values close to 1 by varying q values. Such a power will thus be ignored here.)

Davison and McCarthy (1988) took a different approach to modeling Baum's data. Again accepting the de Villiers-Farley-Fantino punishment model, they suggested that the punisher for changing over could be a timeout

from reinforcement, and hence a loss of reinforcers, from the schedule to which the changeover was being made. Thus, the value of an alternative would be the reinforcers lost from that alternative when changing to it subtracted from the reinforcers gained in that alternative. An appropriate equation is thus:

$$\frac{B_r}{B_g} = c\left(\frac{R_r - \alpha L_{gr}}{R_g - \alpha L_{rg}}\right). \qquad (2)$$

The variables B and R are the same as in Equation 1, with α a scaling parameter included in case lost and obtained reinforcers were unequal in their effects on behavior. L_{gr} measures the reinforcers lost in the transition from the green to red schedules, and L_{rg} is the reinforcers lost in the transition from red to green. The numbers of reinforcers lost from an alternative are calculated from the time spent changing over to that alternative multiplied by the local reinforcer rate on the schedule to which the transition is being made. (Local reinforcer rates are the numbers of reinforcers obtained on a schedule divided by the time spent responding on that schedule.) Notice that this calculation provides the "apparent" number of reinforcers lost during travel to an alternative based on the average rate at which reinforcers were gained locally when the subject is in that alternative. This model accounted quite well for Baum's data and has the added advantage of being able, in theory, to deal directly with unequal travel requirements between patches.

The present study was designed to obtain parametric data on the effects of changeover or travel requirements on concurrent VI VI performance. Fixed-interval (FI) changeover-schedule requirements were used so that the subjects had to spend a fixed period of time, in the absence of the concurrent schedules, changing over between them. The concurrent schedules timed during the changeover, under the assumption that, in a natural environment, prey populations often increase when a patch is not being foraged. In Parts 1 to 3, respectively, FI schedules of 0 s (i.e., a single response was required to change over), 10 s, and 20 s were arranged, and the VI schedules were varied (keeping a constant arranged overall reinforcer rate) at each changeover-schedule requirement. In Part 4, the FI schedule requirements for the two changeovers were made unequal, with one always twice the other.

Keeping the arranged reinforcer rates equal, the absolute values of the changeover schedules were varied. Initially, it may seem that differing travel times, or amounts of work required, for moving alternate ways between patches seems unlikely in nature, but it is not so. For birds, prevailing winds can affect travel times, and for terrestrial animals, patches may be located at different elevations. From both theoretical and naturalistic viewpoints, understanding the behavioral effects of unequal travel times is important. Further, data obtained from such conditions provide stringent tests of quantitative models such as those discussed above.

METHOD

Subjects

Six homing pigeons were maintained at 85% ± 15 g of their ad-lib body weights. They were experimentally naive at the start of the experiment. The subjects were fed the amount of mixed grain necessary to maintain their 85% body weights immediately after the daily training sessions. Water and grit were available at all times in their home cages.

Apparatus

The sound-attenuating experimental chamber was situated remote from a PDP® 11/73 computer that controlled all experimental events using SKED-11® software. An exhaust fan helped mask external noise. The chamber was 340 mm high, 310 mm wide, and 340 mm deep. Three response keys, 20 mm in diameter, 50 mm center to center, and 260 mm from the grid floor were on one wall of the chamber. The magazine aperture (50 mm by 50 mm) was beneath the center key and was centered 130 mm from the floor. Each key could be transilluminated red, green, or white, but only the two outer keys were used in this experiment. During reinforcement, the keylights were extinguished, and the magazine, which was filled with wheat, was raised and illuminated for 3 s.

Procedure

The subjects were deprived of food, trained to eat from the food magazine, and then autoshaped to peck all three response keys, each transilluminated red, green, and white. This took 24 daily sessions. They were then trained on concurrent VI 12-s 12-s schedules arranged

Table 1

Sequence of experimental conditions, number of training sessions, arranged relative reinforcer rate on the red key ($p[R_r]$), FI changeover-schedule values in seconds, and the parts to which each condition contributed. The probability that a reinforcer was arranged was .017 per second throughout.

Condition	Sessions	$p(R_r)$	CO schedules (s)		Part
			r → g	g → r	
1	28	.5	0	0	1
2	30	.9	0	0	1
3	40	.2	0	0	1
4	32	.8	0	0	1
5	25	.1	0	0	1
6	41	.5	10	10	2
7	18	.1	10	10	2
8	25	.8	10	10	2
9	21	.2	10	10	2
10	21	.9	10	10	2
11	51	.5	20	20	3
12	24	.9	20	20	3
13	31	.2	20	20	3
14	37	.7	20	20	3
15	18	.1	20	20	3
16	43	.5	10	10	2
17	37	.5	20	10	4
18	25	.5	10	5	4
19	20	.5	6	3	4
20	23	.5	4	2	4
21	31	.5	2	4	4
22	32	.5	10	20	4
23	18	.5	5	10	4
24	26	.5	3	6	4
25	23	.5	40	20	4
26	30	.5	20	40	4

on the two outer keys; over the next 26 sessions, the schedules were lengthened.

In the experimental procedure used here, which commenced after the above pretraining, the left key was lit white and was designated the switching key. During the experimental session, responses to this key changed, on some schedule, the colors of the right key (either red or green) and the associated VI schedules. The schedules arranged on the switching key and the concurrent schedules arranged on the main (right) key are shown in Table 1. The main-key schedules were arranged nonindependently in the manner of Stubbs and Pliskoff (1969). Every 1 s, a probability gate set at .017 was interrogated. If the result was true, then a reinforcer was assigned to the red main key with a further probability ($p[R_r]$ in Table 1), with a complementary probability to the green main key. The schedules were therefore con-

current exponential schedules. No further re-
inforcer assignments were made until a rein-
forcer that was arranged had been taken. The
schedules continued timing during the time
that subjects were changing over from one
main-key color to the other. There was no
changeover delay.

The reinforcer for right-key responses was
3-s access to grain on both schedules in all
experimental conditions. A houselight pro-
vided general illumination in the chamber.
Sessions ended in blackout after 42 min or after
40 reinforcers had been obtained, whichever
occurred first.

The data collected included the number of
main-key responses on each schedule, the
number of switching-key responses emitted in
changing over from each key to the other key,
the number of reinforcers obtained from each
main-key schedule, and the number of com-
pleted changeovers from the red to the green
main keys. Time-allocation data were also col-
lected, including time spent responding on the
main-key schedules starting from a completed
changeover until the time at which a subse-
quent changeover was initiated, and time spent
changing over from the first response on the
switching key to the response that produced
the alternative main-key schedule. These times
were collected with a 0.1-s resolution and were
converted to whole seconds when the session
ended.

Training continued in each experimental
condition until the subjects had reached a group
stability criterion. The relative main-key re-
sponse rate (red/[red + green]) for each sub-
ject was calculated after each session. If the
median relative response rate over five sessions
was less than .05 different from the median of
the previous (nonoverlapping) set of five ses-
sions, one secondary stability criterion had been
achieved. When this had occurred on five oc-
casions (not necessarily consecutively) for a
subject, that subject had reached its individual
stability criterion. When all subjects had
reached their individual criteria, the experi-
mental conditions were changed for all sub-
jects. Thus, the minimum number of training
sessions per condition was 14. Table 1 shows
the number of sessions that were required to
reach stability in each experimental condition.
Typically, once a subject had reached its in-
dividual criterion, it continued to show stable
performance.

Part 1

In Part 1, each response on the switching
(left) key was effective in changing the sched-
ules and associated stimuli on the main (right)
key. Thus, the changeover schedules were both
FR 1 schedules. The probability of a reinforcer
being assigned to the red main key (relative to
the green main key) was varied over Condi-
tions 1 to 5, with the overall probability of
reinforcement per second set at .017.

Part 2

In this part, both changeover schedules were
FI 10 s. The first peck on the changeover key
darkened the main key, and the changeover
key remained white until a response was emit-
ted after the schedule had completed timing.
That response reilluminated the main key and
provided access to the alternative schedule. The
switching key remained available at all times.
In Conditions 6 to 10, the probability of re-
inforcers being assigned to the red key (relative
to the green) was varied. Condition 16 also
contributed a replication (of Condition 6) to
this part.

Part 3

In Part 3 (Conditions 11 to 15), the change-
over schedules were FI 20 s, and the prob-
ability of red-key reinforcers was varied. Oth-
erwise, the procedure was the same as in
Part 2.

Part 4

This part (Conditions 17 to 26) used a pro-
cedure identical to Parts 2 and 3, but the
changeover schedule arranged for the red-to-
green transition was different from that ar-
ranged for the green-to-red transition. The first
of these was either twice or half the latter (see
Table 1). The smaller changeover schedule
was varied through 2, 3, 5, and 20 s. Each of
these changeover-schedule values was ar-
ranged for both the red and green main-key
schedules in different conditions. The proba-
bility of reinforcement per second was .017,
and the probability that a reinforcer would be
assigned to the red main key was .5 through-
out.

RESULTS

The numbers of responses and seconds spent
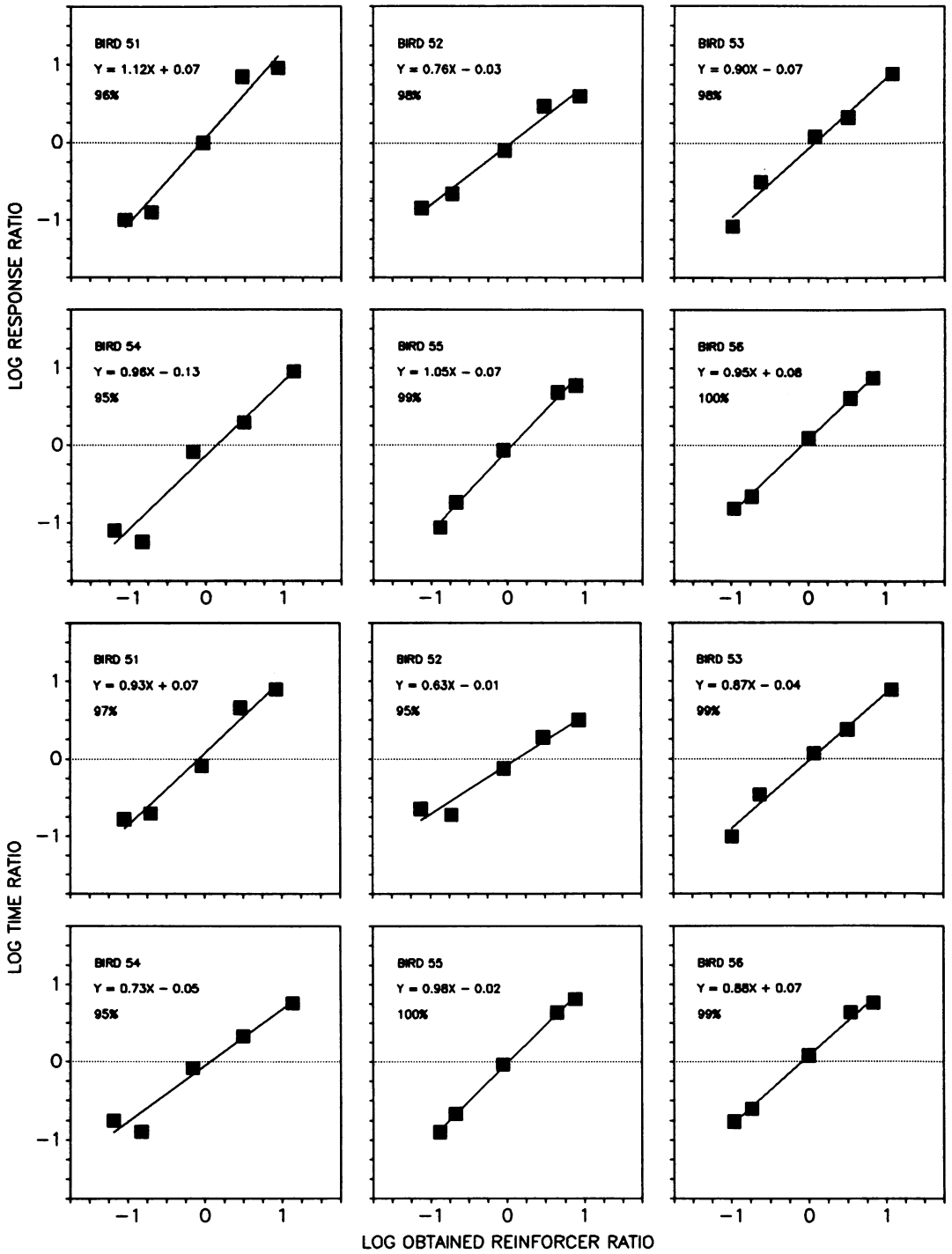responding on both the main-key schedules

Fig. 1. Part 1. Log response ratios (upper panels) and time ratios (lower panels) obtained when a single response was required to change between the concurrent schedules. On each graph is plotted the best fitting straight line, and the equation of the line and the percentage of data variance accounted for are shown on each graph.

Table 2

Results of linear regressions to the response- and time-allocation data obtained in Parts 1 to 3. SE_a is the standard error of the slope estimate, and SE_Y is the standard error of the estimate of the Y prediction. VAC is the percentage of the data variance accounted for.

Bird	Slope (SE_a)	Intercept (SE_Y)	VAC
Part 1: Responses			
51	1.12 (0.13)	0.07 (0.21)	96
52	0.76 (0.05)	−0.03 (0.11)	98
53	0.90 (0.07)	−0.07 (0.12)	98
54	0.96 (0.13)	−0.13 (0.24)	95
55	1.05 (0.06)	−0.07 (0.09)	99
56	0.95 (0.02)	0.08 (0.03)	100
Part 1: Time			
51	0.93 (0.09)	0.07 (1.15)	97
52	0.63 (0.08)	−0.01 (0.06)	95
53	0.87 (0.59)	−0.04 (0.10)	99
54	0.73 (0.09)	−0.05 (0.18)	95
55	0.98 (0.02)	−0.02 (0.03)	100
56	0.88 (0.04)	0.07 (0.06)	99
Part 2: Responses			
51	1.55 (0.06)	0.04 (0.10)	99
52	1.44 (0.10)	−0.04 (0.17)	98
53	1.55 (0.07)	−0.05 (0.11)	99
54	2.18 (0.21)	−0.05 (0.29)	97
55	1.77 (0.11)	0.16 (0.16)	99
56	1.86 (0.14)	0.04 (0.21)	98
Part 2: Time			
51	1.17 (0.07)	−0.02 (0.12)	99
52	1.37 (0.16)	−0.00 (0.28)	95
53	1.13 (0.04)	0.03 (0.07)	99
54	1.50 (0.18)	−0.04 (0.28)	95
55	1.34 (0.16)	0.12 (0.26)	95
56	1.61 (0.15)	0.02 (0.22)	97
Part 3: Responses			
51	1.31 (0.10)	0.05 (0.15)	98
52	1.65 (0.13)	0.10 (0.20)	98
53	1.75 (0.10)	0.16 (0.16)	99
54	2.00 (0.38)	0.32 (0.59)	90
55	1.60 (0.24)	0.11 (0.39)	94
56	1.68 (0.12)	0.01 (0.16)	99
Part 3: Time			
51	0.98 (0.10)	−0.02 (0.14)	97
52	1.32 (0.09)	0.05 (0.13)	99
53	1.28 (0.07)	0.09 (0.13)	99
54	1.56 (0.20)	0.17 (0.31)	95
55	1.33 (0.20)	0.05 (0.32)	94
56	1.37 (0.09)	0.01 (0.13)	99

and the changeover schedules, the numbers of reinforcers obtained, and the numbers of effective changeovers emitted are provided in an appendix, available from the business manager of *JEAB*. In that table, and in what follows, effective changeovers are a count of changeover-key responses that resulted in the red main key being lit. This number is equal to the

effective changeovers to the green main key ± 1.

Figure 1 shows both log response- and time-allocation ratios plotted as a function of log obtained reinforcer ratios for Part 1 for each individual subject. Also shown on these graphs are the best fitting straight lines, obtained by the method of least squares and presented fully in Table 2. The straight lines fit the data very well, with more than 95% of the data variance accounted for. These regressions represent the fits to the generalized matching law (Baum, 1974), which is written:

$$\log\left(\frac{B_r}{B_g}\right) = a \log\left(\frac{R_r}{R_g}\right) + \log c. \qquad (3)$$

B represents responses (or time) allocated, R represents reinforcers obtained, and the subscripts denote the two alternatives. The slope of the fitted line is an estimate of a (sensitivity to reinforcement; Lobb & Davison, 1975), and the intercept is an estimate of log c (bias). Sensitivity averaged 0.96 for response measures and 0.84 for time measures. All response-allocation sensitivities were greater than the corresponding time-allocation sensitivities, a result that is significant on a sign test at $p <$ .05.

Figure 2 shows the data from Part 2 plotted in the same way as those from Part 1 in Figure 1. The data from Condition 16 replicated those from Condition 6 well, with no systematic differences in log response or time ratios being evident. Again, straight lines fit the data well, with more than 97% (responses) or 95% (time) of the data variance accounted for. Mean sensitivity to reinforcement was 1.73 (response allocation) and 1.35 (time allocation), and again all response sensitivity values were greater than time sensitivity values ($p <$ .05). Comparing the results of Parts 1 and 2 (see Table 2), increasing the FI changeover schedule from 0 s to 10 s increased sensitivity for all subjects for both response and time measures (both results significant on a sign test at $p <$ .05).

Figure 3 shows the results of Part 3 plotted as for Parts 1 and 2. Again, straight lines fit the data well, with the exception of Bird 54's response measures, for which data only 90% of the variance was accounted. The mean response sensitivity was 1.67, and the mean time sensitivity was 1.30. Comparing these results with those of Part 1 (Table 2), all subjects showed higher sensitivities for both response and time measures in Part 3 (both results sig-
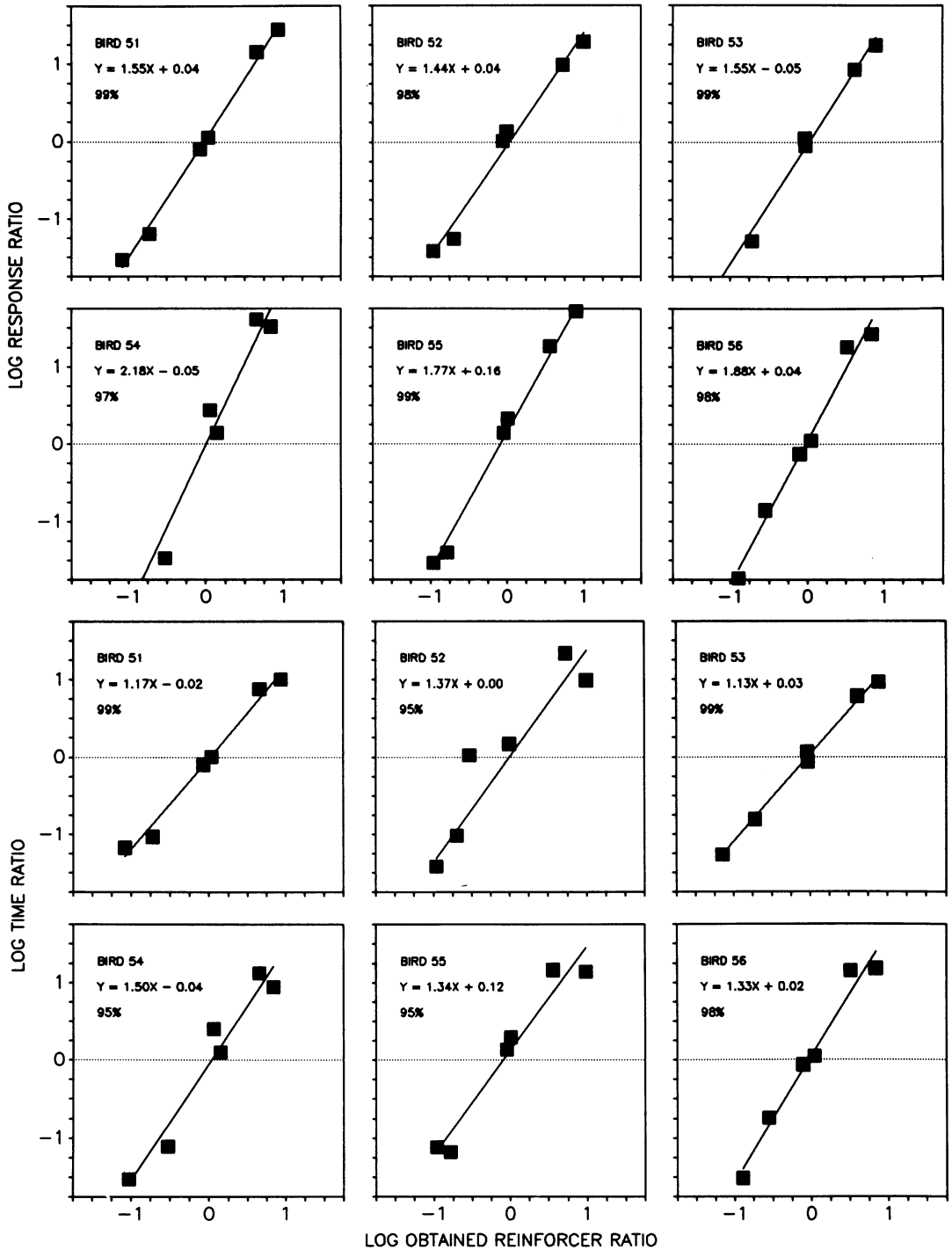
Fig. 2. Part 2. Log response ratios (upper panels) and time ratios (lower panels) obtained when responding on an FI 10-s schedule was required to change between the concurrent schedules. On each graph is plotted the best fitting straight line, and the equation of the line and the percentage of data variance accounted for are shown on each graph. Note that one response data point for each of Birds 53 and 54 is located off the graphs.
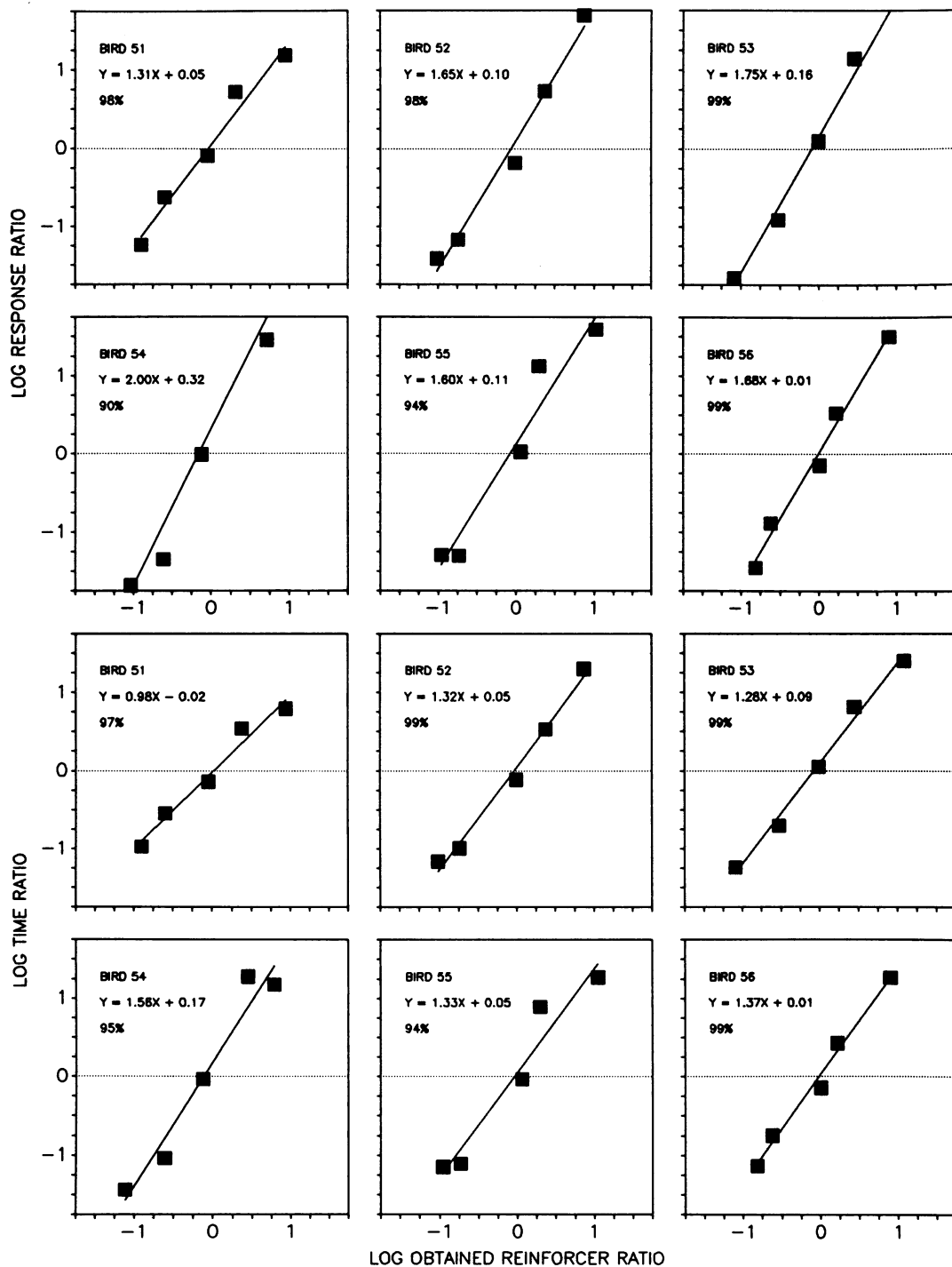
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Fig. 3. Part 3. Log response ratios (upper panels) and time ratios (lower panels) obtained when responding on an FI 20-s schedule was required to change between the concurrent schedules. On each graph is plotted the best fitting straight line, and the equation of the line and the percentage of data variance accounted for are shown on each graph. Again, one response data point for each of Birds 53 and 54 is located off the graphs.

nificant at $p < .05$). However, when the Part 2 and Part 3 results are compared, there was no significant difference. The results suggest, then, that increasing the changeover schedules from FI 10 s to FI 20 s did not increase sensitivity to reinforcement.

Figure 4 shows the mean dwell (or residence) times on each main-key schedule (average time per effective changeover) as a function of the obtained log reinforcer ratio for Parts 1 to 3. The mean results were typical of the individual subjects. All three parts showed the usual effect of log reinforcer ratio, with the smallest dwell times (and thus the highest changeover rates) being produced by equal schedules, and the longest dwell times being emitted on the high reinforcer-rate schedule when the alternative schedule gave a low reinforcer rate. A comparison across Parts 1 to 3 shows that increasing the changeover schedules consistently increased dwell times under all schedule combinations.

The results from Part 4, in which one changeover FI schedule was always twice the other, are shown in Figure 5. There, log response ratios are plotted as a function of the value of the smaller changeover FI schedule. When the red-to-green changeover schedule was twice the green-to-red changeover schedule, subjects emitted more responses on the red main key, and vice versa. Although the group data shown in Figure 5 appear to show a decreasing preference with increasing changeover-schedule requirements, a nonparametric trend analysis of the individual subjects' performances showed that no significant trend existed (Kendall trend test, Ferguson, 1966). For the individuals, there was no significant difference on a sign test ($z = 0.05$) between the preferences shown under the FI 2-s/FI 4-s and FI 20-s/FI 40-s conditions. Exactly the same conclusion can be drawn from the time-allocation data. On average, the difference between the two functions for responses and the two for times suggests that the more difficult it is to leave a schedule, the longer a subject remains on the schedule.
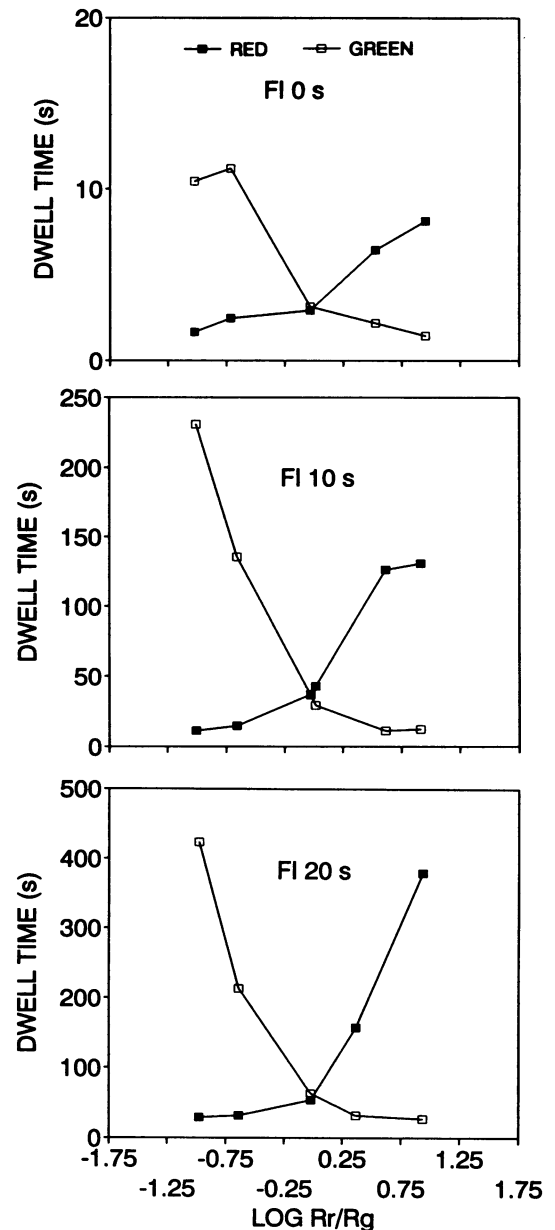

Fig. 4. Mean dwell (residence) times in seconds on the main-key schedules as obtained log reinforcer ratios were varied over Parts 1 (0-s changeover schedules) to 3 (20-s changeover schedules). Dwell time is the average time spent on the main key per effective changeover.

DISCUSSION

The results of the present experiment were consistent with, and extend, previous results on preference in the face of differing ease of changing over. Like the results of Baum (1982), increasing the difficulty of changing between concurrently available schedules increased, at least initially, the sensitivity of both response and time allocation to the obtained distribution of reinforcers. At FI 0 s mean response sensitivity was 0.96, and at FI 10 s it was 1.73. The respective values for time allocation were
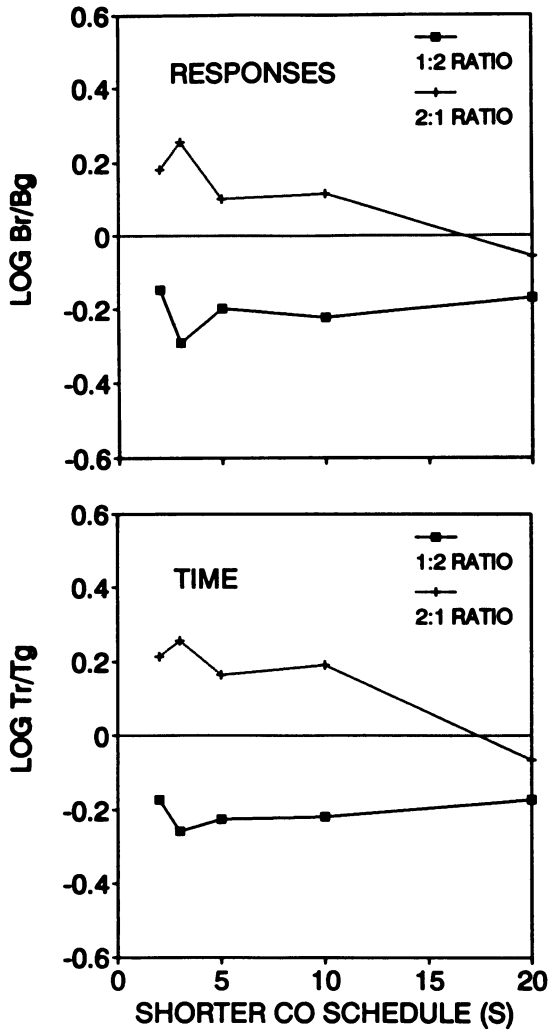
Fig. 5. Part 4. Mean log response ratios (upper panel) and log time ratios (lower panel) as a function of the smaller FI changeover schedule. The other changeover schedule was always twice that plotted. Arranged main-key reinforcer rates were arranged to be equal.

0.84 and 1.35. However, by arranging three (rather than two) quantitative (rather than qualitative) levels of changeover requirements, I showed that increasing the changeover requirement from FI 10 s to FI 20 s did not further significantly increase either response or time sensitivity to reinforcement. At FI 20 s, mean sensitivity was 1.67 for responses and 1.30 for time measures. The present results are also consistent with those of Pliskoff et al. (1978), who arranged fixed-ratio (FR), rather than FI, schedules on changing over. They also

arranged only two levels (FR 5 and FR 10) and found an increase in sensitivity between them.

The present results differed from previous results in one notable way: Time-allocation sensitivity was always less than response-allocation sensitivity. For schedules based on arithmetic progressions, Taylor and Davison (1983) reported that time allocation was generally more sensitive than response allocation, whereas for schedules based on exponential progressions, there was no reliable difference. There seemed to be no unusual features of the present procedure that could have caused this result.

It is reasonable to assume that increasing the changeover FI schedules from 10 to 20 s would have increased (but possibly not doubled) the punishing effects of changing over. But this change did not increase sensitivity to reinforcement. This finding at first seems to be incompatible with any sort of punishment model (Equations 1 and 2), but, as I will show, this is incorrect.

Equation 1 relates concurrent-schedule response distributions to concurrent-schedule reinforcer rates and the work required to change between the schedules. For this equation to describe the present data, in particular the failure of sensitivity to reinforcement to increase between the FI 10-s and FI 20-s changeover schedules, one of two conditions (or a combination of these conditions) must apply. Either the cost q of changing over must remain the same between the FI 10-s and FI 20-s changeover-schedule conditions, or the changeover rate C_{ij} must fall to keep the overall amount of punishment constant. Figure 4 showed that there were substantial increases in dwell times on the main-key schedules between the FI 10-s and FI 20-s schedules and hence decreases in C_{ij} as required by this model. Thus, the model may be viable. The problem for this model, however, is that q is a variable, and the function relating q to changeover requirements has not been determined. With a set of data obtained using varied changeover requirements (as those reported here), a best fitting value of q would have to be found for each different pair of changeover schedules. This could result in a good fit to the data, but the effective number of free parameters will necessarily be large. Thus, below, I reinterpret this model. In the present experiment, the

amount of work done in changing over was measured directly as the number of responses on the changeover keys. Thus, in line with the general approach of Baum's model, I assessed a model in which a linear function of the work done was subtracted from the reinforcers obtained on each key. Such a model seems to be in the spirit of Baum's model and has the advantage of not requiring a different q parameter for each pair of changeover schedules.

The model suggested by Davison and Mc-Carthy (1988) needs a little more interpretation than they originally gave it before it can be assessed. How should reinforcers lost be calculated? In the Introduction, their suggestion was interpreted in this way: When a subject commences a changeover, reinforcers are "lost" on a key calculated as the time spent changing over to that key times the local reinforcer rate on that key. Davison and Mc-Carthy were less than clear about their use of Equation 2, and it appears that they used overall reinforcer rates on the keys rather than local reinforcer rates. Would Equation 2, as interpreted here, predict no change in sensitivity between the FI 10-s and FI 20-s changeover schedules? The decreasing changeover rate between the FI 10-s and FI 20-s conditions, coupled with the increasing time spent changing over, could lead to a prediction of no decrease. Hence, that model can also potentially describe the present data.

Consistent with Equations 1 and 2 as interpreted above, the results of Part 4 showed that the subjects emitted more responses (and spent more time) on the key to which it was easier and quicker to change, but more arduous and slower to leave. For example, if the red-to-green changeover schedule was FI 2 s and the green-to-red schedule was FI 4 s, the subject emitted more responses on the green schedule. This could be seen variously as losing more effective reinforcers on the transition to the red key than on the transition to the green key, or greater punishment through the greater work required to move from green to red. All the present data, then, are in qualitative agreement with Equations 1 and 2. Which equation predicts better quantitatively?

One difficulty in choosing between work and reinforcer-loss accounts of performance is that, because FI changeover schedules were used here, the work required for changing over (the numbers of FI responses emitted) is likely to

Table 3

Linear regressions between the predictions of Equations 1 and 2 and the obtained log response ratios over all conditions of the experiment. VAC is the percentage of data variance accounted for by the predictions, not by the fitted line. The numbers under the column headed "Exclusions" (reinforcer-loss model) are the numbers of data for which infinite predictions were made and which therefore were dropped from the analysis. w (work model) is the best estimate of the number of reinforcers equivalent to one changeover response.

Reinforcer-loss model				
Subject	Slope (SD)	Intercept	VAC	Exclusions
51	0.98 (0.04)	0.01	96	0
52	0.73 (0.06)	0.00	77	5
53	0.75 (0.04)	−0.05	83	4
54	0.96 (0.04)	−0.04	96	2
55	1.01 (0.04)	0.03	96	0
56	1.02 (0.05)	−0.03	95	3

Work model				
Subject	Slope (SD)	Intercept	VAC	w
51	1.15 (0.06)	0.01	91	0.007
52	1.22 (0.11)	0.06	82	0.001
53	1.06 (0.07)	−0.07	89	0.011
54	1.39 (0.16)	0.02	69	0.006
55	1.04 (0.07)	0.08	90	0.016
56	1.14 (0.09)	−0.02	85	0.011

be strongly correlated with the times spent changing over.

Reinforcer-Loss Model

Table 3 shows quantitative fits to the data from the present experiment according to Equation 2 as interpreted above, and the obtained data are plotted against the predictions in Figure 6. Figure 6 also shows the locus of perfect prediction for Equation 2. The value of α was taken as 1, and hence no free parameters were required. For 4 individuals, and for the group data, some conditions resulted in small negative net reinforcers obtained, and these data were simply dropped from the analysis. The discarded data were generally from extreme log reinforcer-ratio conditions. The numbers of conditions thus excluded for each bird are shown in Table 3. The slope obtained from a linear regression between obtained and predicted log response ratios was close to 1.0 for 4 (Birds 51, 54, 55, & 56) of the 6 subjects, and the percentage of data variance accounted for was high for these subjects. For Birds 52 and 53, the slopes were lower (showing un-
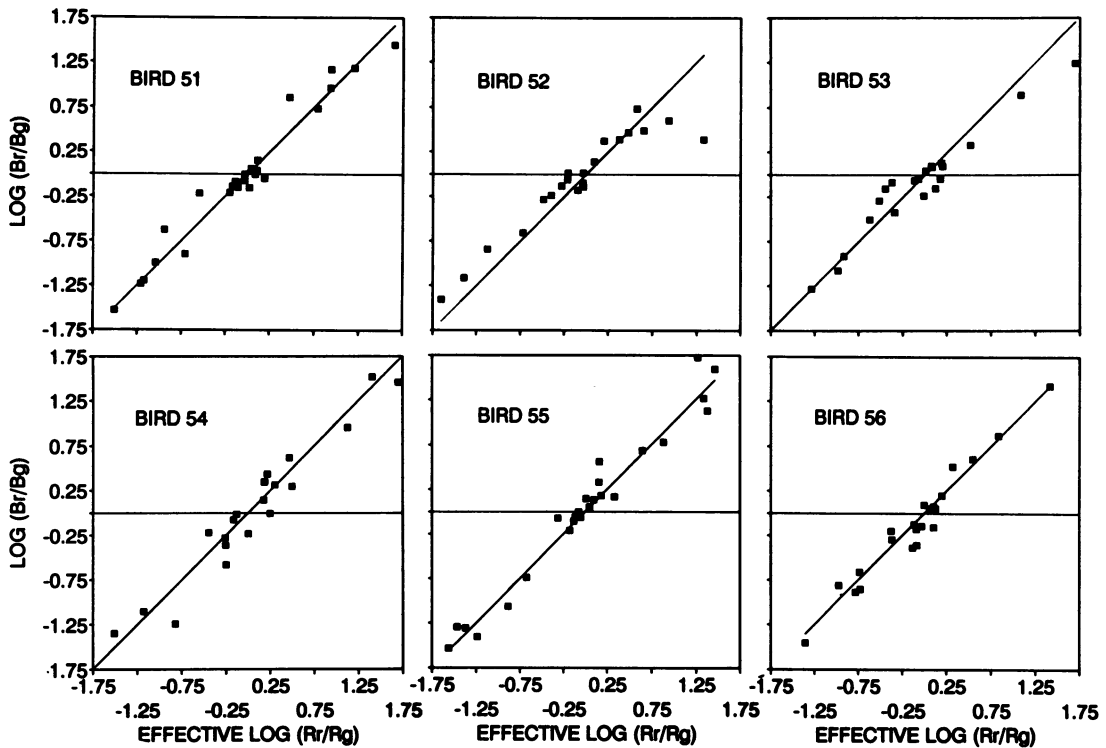
Fig. 6.   Log response ratios as a function of the predictions of the model given as Equation 2. Not all data were plotted (see Table 3 and text). The plotted straight lines are the lines of perfect prediction.

derprediction of performance), and percentages of variance accounted for were also lower. As Figure 6 shows, the major reason for the lower slope for Bird 52 was the very considerable overprediction of preference in Condition 20, in which the reinforcer schedules were equal and the changeover schedules were FI 2 s and FI 4 s. The obtained preference in this condition was relatively small.

These results point up one important corollary of Equation 2: As overall reinforcer rates fall, or as lost reinforcers become large (i.e., as net obtained reinforcers fall), predictions necessarily become more inaccurate because large differences in net reinforcers can occur. At the limit, of course, when the net reinforcer rate is zero, the net ratio becomes infinite. For Bird 52, the data also showed consistent overprediction at the three largest negative log response-ratio predictions. The data from Bird 53 fell as close to perfect prediction as the data from Birds 51, 54, 55, and 56 over most of the range, with the largest deviation occurring for the greatest log response-ratio prediction (Condition 7, equal FI 10-s changeover sched-

ules, relative reinforcer rate .1). It was Subjects 52 and 53 that showed the lowest sensitivities to reinforcement in Part 1 (Table 1, Figure 1), and the overprediction in the model may represent fundamental undermatching in these subjects. Indeed, the slopes of the fits from all conditions (except those discarded) of predicted versus obtained data (Table 3) were not significantly different (sign test) from the fits to the five conditions comprising Part 1 (Table 2). In general, then, Equation 2 with no free parameters did a very good job of predicting performance for most subjects. It would have predicted better had a sensitivity-type parameter been used to raise to a power all of the equation to the right of the equality in Equation 2 (i.e., the predictions). However, the increase in predictive accuracy gained would have been at the expense of a free parameter and could be justified for only Birds 52 and 53. The further addition of a bias parameter may also help the prediction, but because the intercepts of the fitted lines in Table 3 were very small, the benefits would have been slight.

The occasional negative net reinforcers pre-

dicted by the local reinforcer rate model above suggest some alternatives. Perhaps what is being lost during travel is a reinforcer rate based on the overall reinforcer rate on a schedule or on the total reinforcer rate in the session. However, both such models severely underpredict preferences and will not be further discussed. A more likely explanation of negative net reinforcers is the use, here, of dependent concurrent VI VI schedules. In such schedules, preference cannot become extreme without all reinforcers becoming unavailable, so there is some additional reinforcement for changing over inherent in the procedure. The presumption is that conditions that gave negative net reinforcers would have produced exclusive choice if independent, rather than dependent, scheduling had been used. This could be handled quantitatively by adding a constant, R_c, to the numerator and denominator of Equation 2 to represent the constant value of changing over. Such a modification would not only eliminate the occasional obtained negative net reinforcer frequencies but would also have the added advantage of being able to describe the fundamental undermatching in the relation between log response (or time) measures and log obtained reinforcer ratios that occurred for Birds 52 and 53. Such a model can be fit iteratively to the present data, but it was thought too speculative to pursue here.

A second possibility for negative net reinforcer frequencies is that Equation 2 is an approximation to a more molecular model that could take into account the fact that, after completing a changeover, there is a momentarily high probability of reinforcement, leading to a discounting of the reinforcers lost during the changeover.

Work Model

Equation 1 as interpreted above, in which punishment arises from the work needed to change between the schedules, requires a scaling parameter to relate work done to reinforcer frequency. I will call this parameter w. It measures the number of reinforcers that are equivalent to one changeover response. The best fitting value of this parameter was found iteratively, and the regressions of the data against the resulting predictions are also shown in Table 3. Figure 7 compares the predictions of the reinforcer-loss and work models for data averaged over all 6 subjects. The reinforcer-loss
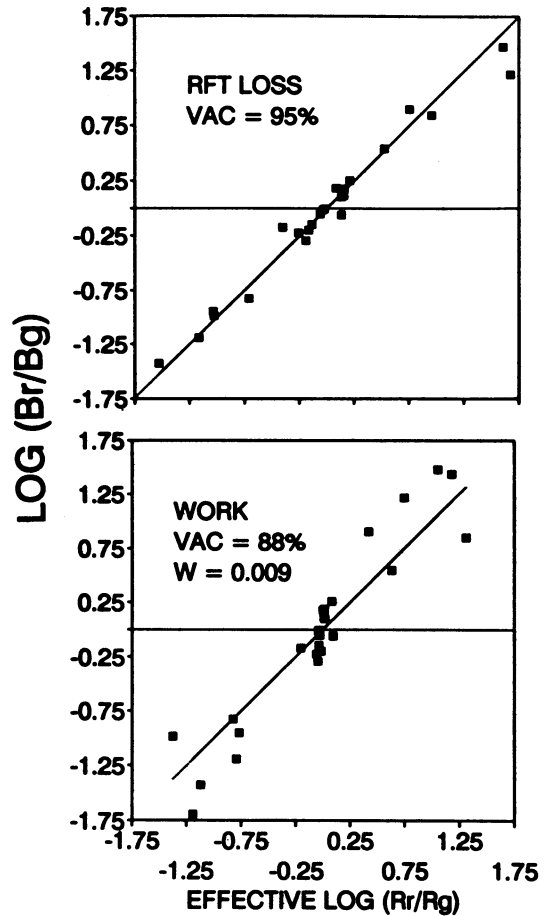

Fig. 7. Predictions of the reinforcer-loss model (upper graph) and work model (lower graph) for the data averaged across all subjects. For the work model, a best fitting value of $w = 0.009$ was used.

model accounted for more of the data variance for all subjects except 52 and 53, and the fits to this model were more satisfactory in terms of the standard deviation of the slope estimate for all subjects. For the group data (Figure 7), the reinforcer-loss model accounted for considerably more of the data variance, and the predictions were obviously better. Taking into account the free parameter in the work model, the reinforcer-loss model is to be preferred quite strongly over the work model.

There are a number of experimental results that support the conclusion that amount of work often does not control choice. For instance, when pigeons choose between equal fixed times to reinforcers, there is no preference for the alternative that requires less work
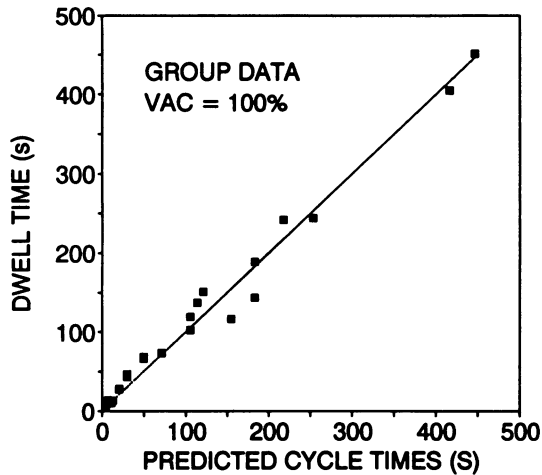
Fig. 8. Dwell (or residence) times on the main-key schedules predicted by Equation 4 with $b = 1$, $G = 1$ s, and $e = 0.6$. See text for further explanation.

(Davison, Alsop, & Denison, 1988; Moore & Fantino, 1975; Neuringer, 1969). Lack of control by work within concurrent VI VI schedules also has been demonstrated by Vaughan and Miller (1984) and by Boelens (1984). It is interesting to speculate on the basis of these results whether reinforcer loss, rather than work done in traveling, may be a source of control of patch residence and giving-up times in natural foraging environments. I have not been able to locate any papers in the behavioral ecology literature that provide data on this question.

Predicting Dwell Times

Dwell times (or residence times, or giving-up times) have been the focus of considerable research in the foraging literature (e.g., Stephens & Krebs, 1986), but little work seems to have been done on the effects of distance between patches on residence times. However, in the behavioral literature, data have been reported, and models to predict dwell times have been suggested. Hunter and Davison (1978) compared a number of models of changeover performance (the reciprocal of the dwell time summed across the alternatives, or the cycle time). Having found extant models lacking in various ways, Hunter and Davison suggested a series of models for predicting changeover rates from response, time, and reinforcer distributions. I shall concentrate here on the last of these, which was shown to pro-

vide good descriptions of a wide variety of experimental data.

The equation offered by Hunter and Davison (1978) was:

$$C_{ij} = b[(T_{ij} + G)(T_{ji} + G)]^e \frac{R_i R_g}{(\Sigma R)^2}. \quad (4)$$

In this equation, C_{ij} is the changeover rate and b, G, and e are constants. In the present application, b was taken as 1. The constant G is the minimum time taken to move between the schedules when no changeover delay is imposed—in the present case, this refers to the minimum time taken to move from the main key to the changeover key and back. The value of G was taken as 1 s. The variable T is, in Hunter and Davison's approach, the duration of the changeover delay. For these variables, I used the arranged changeover schedule duration. I used the reciprocal of Equation 4 to predict cycle times (the sum of times spent responding on the two main keys per changeover, excluding changeover times) in seconds and informally iterated for a best value of e using group data. An e value of -0.6 was best, reasonably close to the mean e value (-0.53), and well within the range of values calculated by Hunter and Davison for seven previous experiments comprising 20 fits (see their Table 4). Equation 4 with these constant values predicted the cycle times with 100% of the data variance accounted for using all 26 experimental conditions. The predictions are shown in Figure 8. The fit is particularly impressive because the range of dwell or residence times in this experiment was very great. Equation 4 also, of course, predicts that cycle times will be greater the more different are the main-key schedules (Figure 4).

Given that behavior distributions are well described by the reinforcer-loss model discussed above and that overall cycle times are well described by Hunter and Davison's (1978) equation, individual dwell or residence times as a function of both relative reinforcer rates and changeover contingencies can be predicted. As Baum (1982) suggested, changeover schedules and travel are functionally equivalent to changeover delays in their effects on concurrent-schedule performance.

In summary, a reinforcer-loss model with no free parameters accounted very well for a wide range of concurrent-schedule perfor-

mances with widely differing changeover-schedule requirements. Increasing travel time increases the sensitivity of behavior distributions to reinforcer distributions, but only so long as changeover frequencies remain constant: If these fall, so will sensitivity fall. Changeover frequencies themselves were well described by Hunter and Davison's (1978) changeover model. This latter model has two free parameters: One of these, the minimum travel time *G*, is severely constrained; the other, *e*, is not fully understood but appears to be constant across studies. Perhaps the most important question now is whether this combination of models can predict patch residence times as a function of relative and absolute prey frequency and travel in natural environments in which the distributions of prey in time may be very different from those used here and in most laboratory research.

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