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ON THE RELATION BETWEEN PREFERENCE AND RESISTANCE TO CHANGE

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Nevin (1979) noted that preference in concurrent chains and resistance to change in multiple schedules were correlated, in that both measures were affected similarly by variations in parameters of reinforcement such as rate, immediacy, and magnitude. To investigate the relationship between preference and resistance to change directly, we used a within-session procedure that arranged concurrent chains in one half of the session and a multiple schedule in the other half. The same variable-interval schedules served as terminal links in concurrent chains and as the components of the multiple schedule, and were signaled by the same stimuli. After performances had stabilized, responding in the multiple schedule was disrupted by delivering response-independent reinforcement during the blackout periods between components. Both preference in concurrent chains and relative resistance to change of multiple-schedule responding were well described as power functions of relative reinforcement rate, as predicted by current quantitative models (Grace, 1994; Nevin, 1992b). In addition, unsystematic variation in preference and resistance to change was positively correlated, which suggests that preference and resistance to change are independent measures of a single construct. That construct could be described as the learning that occurs regarding the prevailing conditions of reinforcement in a distinctive stimulus situation.

Key words: resistance to change, multiple schedules, choice, concurrent chains, response strength, key peck, pigeons

Based on an analogy to Newtonian mechanics, behavioral momentum theory (Nevin, 1992b; Nevin, Mandell, & Atak, 1983) identifies two independent dimensions of operant behavior: resistance to change and response rate. Resistance to change is analogous to mass, and response rate is analogous to velocity; their product is behavioral momentum. Although response rate and resistance to change often covary, their independence has been demonstrated in a number of studies employing a variety of multiple schedules (Nevin, 1984, 1992a; Nevin, Smith, & Roberts, 1987; Nevin, Tota, Torquato, & Shull, 1990). The general conclusion has been that response rate is determined primarily by operant response–reinforcer contingencies, whereas resistance to change is determined by Pavlovian stimulus–reinforcer contingencies. Resistance to change is measured as the reciprocal of the rate of decrease in response rate when a disrupter such as extinction, satiation, or response-independent food is applied.

The independence of response rate and resistance to change resembles the dissociation, in some studies employing the concurrent-chains procedure, between preference for a terminal-link schedule and response rate during that terminal link. For example, Herrnstein (1964) found that preference, measured as relative initial-link response rate, for variable-interval (VI) versus variable-ratio (VR) terminal links approximately matched relative reinforcement rate, although response rates in the VR terminal links were much higher. Similarly, Neuringer (1969) obtained indifference between equal-valued fixed-interval (FI) and fixed-time (FT) terminal links, despite a higher response rate during the FI. In general, preference in concurrent chains is determined by the rate (or immediacy) of reinforcement from terminal-link onset, whereas terminal-link response rate depends on the terminal-link schedule (i.e., the response–reinforcer contingency). Preference in concurrent chains thus appears to be similar to resistance to change in multiple schedules, because both depend primarily on stimulus–reinforcer contingencies.

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The similarities between preference and resistance to change extend to the variables that determine them. Nevin (1979) noted that the parameters of reinforcement that increase resistance to change (e.g., relatively greater rate, immediacy, or magnitude of reinforcement) also increase preference for a terminal link in concurrent chains. He further noted that because terminal links were presented successively and were mutually exclusive, concurrent chains could be construed as measuring choice between components of a multiple schedule. All these similarities suggest that resistance to change and preference may be independent measures of a unitary construct that has been termed *response strength* or *behavioral mass* in the multiple-schedules literature and *conditioned reinforcement value* (or simply, *value*) in the concurrent-chains literature. Here we describe a new method for obtaining measures of resistance to change and preference within conditions and within subjects, and present parametric data on their relationship, which is predicted by recent quantitative models.

A Relation Between Preference and Resistance to Change

When different VI schedules are arranged in the components of a standard two-component multiple schedule, the ratio of steady-state response rates is a power function of the ratio of reinforcer rates (Lander & Irwin, 1968):

$$\frac{B_1}{B_2} = \left(\frac{R_1}{R_2}\right)^a, \qquad (1)$$

where B_1 and B_2 are response rates and R_1 and R_2 are reinforcer rates in Components 1 and 2. Typically, the value of a, the sensitivity of response-rate ratios to reinforcement-rate ratios, is about 0.33 (see Davison & McCarthy, 1988; McSweeney, Farmer, Dougan, & Whipple, 1986, for review).

Nevin (1992b) reviewed a number of two-component multiple-schedule studies that examined resistance to change when responding was disrupted by prefeeding, intercomponent food, or extinction. No single study contributed more than three data points, precluding confident estimation of function form or parameter values. However, average data aggregated across experiments were acceptably described by a power function with a_m, the sensitivity of resistance ratios to reinforcer-rate ratios, about 0.35. Accordingly, the relation between the resistance ratio (or the ratio of behavioral masses), m_1/m_2, and the ratio of reinforcer rates may be written:

$$\frac{m_1}{m_2} = \left(\frac{R_1}{R_2}\right)^{a_m}. \qquad (2)$$

Because baseline response rate and resistance to change in multiple schedules are related to reinforcement by similar functions, it might appear that both are measuring the strength of discriminated operant behavior. There are several results, however, suggesting that response rate and resistance to change are separate and independent aspects of behavior. First, increasing the time between components reduces sensitivity of response-rate ratios to reinforcer-rate ratios, but has no effect on resistance ratios (Nevin, 1992a). Second, in serial schedules, response rate is inversely related to reinforcer rate in the following component, but resistance to change is positively related to reinforcer rate in the following component (Nevin, 1984; Nevin et al., 1987; Williams, 1991, has obtained a similar result for preference in extinction probe tests). Third, adding response-independent reinforcers, or reinforcers that are contingent on an alternative response, to one component of a multiple schedule with the same VI schedule in both components reduces response rate but increases resistance to change in that component (Nevin et al., 1990). These findings demonstrate the independence of steady-state response rate and resistance to change.

Nevin (1992b) showed that all of these resistance data were consistent with a model that expressed resistance to change as a function of the stimulus–reinforcer contingency, calculated as the ratio of the reinforcer rate in a target component relative to the reinforcer rate in the session as a whole. If the reinforcer rate in the session is the same for both components, as in standard two-component multiple schedules, the ratio of contingency ratios reduces to the reinforcer-rate ratio for comparisons of resistance to change (Equation 2). By contrast, the foregoing studies suggest that steady-state response rate is determined by the rate of reinforcement that is correlated with a response relative to alternative reinforcement in the same or successive components (a response–reinforcer contingency; cf. Williams & Wixted, 1986). In two-component multiple VI VI schedules, the relative rate of reinforcement for a response and the relative rate of reinforcement correlated with a stimulus may be the same, with the result that both response rate and resistance to change are similarly related to reinforcement. However, these relations arise from separate processes and do not reflect a unitary construct.

Relative rate of reinforcement (expressed equivalently as immediacy) has also been implicated as a determiner of preference in concurrent chains. Grace (1994) followed up on two suggestions made by Davison (1983): (a) that a model for concurrent chains be based on the generalized matching law and (b) that terminal-link value be treated analogously to reinforcer magnitude in concurrent schedules, and thus represented as a concatenated ratio (Baum, 1974; Baum & Rachlin, 1969). Given these assumptions, Grace showed how effects on preference of temporal context (i.e., variation in relative initial- and terminal-link duration) that had proven to be troublesome for previous models (Davison, 1987), could be incorporated naturally:

$$\frac{B_L}{B_R} = b\left(\frac{R_{1L}}{R_{1R}}\right)^{a_1}\left[\left(\frac{1/D_L}{1/D_R}\right)^{a_2}\left(\frac{X_L}{X_R}\right)^{a_x}\right]^{\left(\frac{Tt}{Ti}\right)^k}. \quad (3)$$

According to Equation 3, which is the most general form of the contextual choice model, relative initial-link responding between the left and right keys (B_L/B_R) matches the relative rates of entry into the terminal links (R_{1L}/R_{1R}), with bias (b) and sensitivity (a_1) parameters as in the generalized matching law. Relative terminal-link value is represented by the ratios inside the large brackets, and is determined by the relative immediacy (i.e., reciprocal of delay) of reinforcement from terminal-link onset $[(1/D_L)/(1/D_R)]$ and a potential second variable X (e.g., reinforcer magnitude), with sensitivity parameters a_2 and a_x, respectively. The novel feature of the contextual choice model is that the terminal-link ratios are raised to an additional exponent, $(Tt/Ti)^k$, where Tt and Ti are the average times spent in the terminal and initial links per reinforcer, and k is a scaling parameter. This additional exponent allows the model to predict temporal context effects: Because the effective sensitivity to reinforcement immediacy is $a_2(Tt/Ti)^k$, preference for a constant pair of terminal links will decrease if initial-link duration increases (Fantino, 1969), and conversely, preference for a pair of terminal links will increase, if with constant initial links, the immediacy ratio is held constant while absolute terminal-link duration increases (MacEwen, 1972). Grace (1994) showed that Equation 3 (generally with k = 1) gave an excellent description of a wide range of concurrent-chains data, accounting for an average of 90% of the variance in relative initial-link responding across 19 studies. Because the contextual choice model reduces to the generalized matching law in the limit as Tt approaches zero, these models may be considered to be a single descriptive model applicable to both concurrent schedules and concurrent chains.

If terminal-link entries are equated through the use of interdependent initial-link scheduling (Stubbs & Pliskoff, 1969), if temporal context is controlled by arranging constant Tt and Ti across experimental conditions (which, in effect, subsumes Tt/Ti in a_2; Grace, 1995), and if rate (i.e., immediacy) of reinforcement is the only terminal-link independent variable, then Equation 3 reduces to

$$\frac{B_L}{B_R} = b\left(\frac{R_{2L}}{R_{2R}}\right)^{a_2}, \quad (4)$$

where R_{2L} and R_{2R} are the terminal-link reinforcement rates. According to Equation 4, preference is a power function of relative reinforcement rate. But if both preference and relative resistance to change (Equation 2) are power functions of relative reinforcement rate, then preference and relative resistance to change must be related by a power function whose exponent is the ratio of exponents relating each to relative reinforcement rate. Specifically, Equations 2 and 4 can be combined to yield

$$\frac{m_L}{m_R} = b'\left(\frac{B_L}{B_R}\right)^{a_m/a_p}, \quad (5)$$

where, for sake of clarity, sensitivity exponents for preference and relative resistance are noted by a_p and a_m, respectively, and $b' = 1/b^{a_m/a_p}$. Equation 5 states that preference for a terminal-link schedule and resistance of responding during that terminal link will be related by a power function, thus underscoring Nevin's (1979) observation that terminal links in concurrent chains are analogous to the components of a multiple schedule.

The only previous data that have compared resistance to change and preference within subjects were reported by Nevin (1979; but see also Mandell, 1980). He described an experiment with the same subjects that had served in Experiment 5 of Nevin (1974). That experiment arranged multiple schedules in which responding was reinforced according to VI schedules with tandem differential reinforcement of high or low rate requirements (DRH or DRL). Although the data were somewhat variable across subjects, Nevin (1974) found that for 2 pigeons, DRL responding was more resistant to response-independent food and extinction than was DRH responding, with reinforcement rates equated (Blackman, 1968; Lattal, 1989). Nevin (1979) then used the same subjects to test preference in concurrent chains for identical VI terminal links with tandem DRL or DRH. All subjects showed a preference for the DRL terminal link (Fantino, 1968), but significantly, the 2 pigeons that had demonstrated greater resistance for DRL in Nevin (1974) showed the greatest preference for the DRL terminal link, suggesting that the measures may be correlated within subjects.

To examine parametrically the relationship between preference and resistance to change embodied in Equation 5, we conducted an experiment with pigeons that employed a new method for obtaining both measures within conditions and within subjects. In one half of each experimental session a concurrent-chains procedure was arranged. During the initial links the side keys were illuminated white, and terminal-link entry was signaled by illuminating the center key either red or green. Responding during the terminal links was reinforced according to separate VI schedules. The other half of each session was a multiple schedule, in which the components were signaled by the same stimuli as the concurrent-chains terminal links and the same schedules were in effect. Components of the multiple schedule were separated by a 30-s intercomponent interval (ICI). After performances had stabilized, responding in the multiple schedule was disrupted by presenting response-independent food during the ICI, according to a variable-time (VT) schedule. In this way, separate measures of preference and relative resistance to change for the same pair of schedules were obtained in each of the eight conditions of the experiment.

METHOD

Subjects

Four White Carneau pigeons, numbered 29, 30, 32, and 28, participated as subjects, and were maintained at 85% ad libitum weights ±15 g by limiting access to food. All had previous experience with a variety of experimental procedures. Subjects were housed individually in a vivarium with a 12:12 hr light/dark cycle (lights on at 7:00 a.m.), and had free access to water and grit.

Apparatus

Four standard three-key operant conditioning chambers, 35 cm deep by 35 cm wide by 35 cm high, were used. The keys were 26 cm above the floor. The side keys could be transilluminated white, and the center key could be transilluminated red or green. Each chamber was equipped with a houselight 7 cm above the center key for ambient illumination and a grain magazine with an aperture (6 cm by 5 cm) 13 cm below the center key. The magazine was illuminated when wheat was made available. A force of approximately 0.10 N was required to operate each key, which resulted in an audible feedback click. Chambers were enclosed in sound-attenuating boxes and fitted with ventilation fans for masking extraneous noises. The experiment was controlled and data were collected using a MED-PC® system interfaced to an IBM®-compatible microcomputer located in an adjoining room.

Procedure

Because subjects were experienced, training commenced immediately in the first condition. All sessions consisted of a concurrent-chains procedure in one half of the session and a multiple schedule in the other half. Session halves were separated by a 3-min blackout. The houselight was illuminated throughout the session except during reinforcement and the 3-min blackout. The order of the concurrent chains and multiple schedule varied randomly from day to day, except for test sessions when response-independent food was presented during the multiple schedule (see below), in which the concurrent chains always occurred first. Sessions were conducted 7 days a week at approximately the same time of day (4:00 p.m.).

Concurrent-chains procedure. The concurrent-chains procedure consisted of 36 initial-link and terminal-link cycles. Reinforcement was delivered at the end of each cycle. At the start of a cycle, the side keys were illuminated white to signal the initial links. A terminal-link entry was assigned randomly to either the left or right key, with the restriction that exactly 18 entries to each terminal link were arranged in the session. An initial-link response was reinforced by terminal-link entry provided that (a) it was to the preselected key; (b) an interval selected from a VI 20-s schedule had elapsed; and (c) a 1.5-s changeover delay (COD) was satisfied (i.e., at least 1.5 s had elapsed following a changeover to the side that terminal-link entry was arranged).

The VI 20-s initial-link schedule did not begin timing until the first peck to either key occurred. This allowed postreinforcement pauses to be excluded from initial-link time. The VI 20-s schedule contained 18 intervals constructed from an arithmetic progression, a, $a + d$, $a + 2d$, . . ., in which a equals one 18th and d equals one ninth of the schedule value. The intervals were sampled such that all 18 intervals preceded left and right terminal-link entries exactly once per session.

Terminal-link entry was signaled by illuminating the center key either red or green, coupled with extinguishing the side keylights. For Birds 29 and 32, the terminal link that was produced by a left initial-link response was signaled by red on the center key, and the terminal link that was produced by a right initial-link response was signaled by green on the center key. This assignment was reversed for Birds 30 and 28. Terminal-link responses were reinforced according to VI schedules that contained 18 intervals constructed from exponential progressions (Fleshler & Hoffman, 1962). The terminal-link VI schedules were sampled such that each interval was selected exactly once per the concurrent-chains portion of the session. When a terminal-link response was reinforced, the keylight and houselight were extinguished, and the grain magazine was raised and illuminated for 2.5 s. After reinforcement the houselight and initial-link keylights were reilluminated and the next cycle began, unless the 36th reinforcer in the session half had just been delivered, in which case either the session ended or a 3-min blackout began, followed by the multiple schedule. All nonreinforced responses (initial and terminal link) produced a 0.05-s darkening of the key as feedback.

Multiple schedule. The multiple schedule consisted of 36 separate components. There were two types of components, defined by the color of center-key illumination. Each component occurred 18 times in a session, terminated when a single reinforcer had been delivered, and was preceded by a 30-s ICI, during which the houselight was on. The ICI was set at 30 s to be approximately equal to the time spent in the initial links, per cycle, in concurrent chains. At the start of a component, the center key was illuminated red or green, and an interval from a VI schedule began timing. The VI schedule for each component was identical to that during the concurrent-chains terminal link signaled by the same center-key color. Intervals from the VI schedules were sampled such that each occurred once per the multiple schedule session half. When the interval had timed out, the next response on the center key extinguished the keylight and houselight, and the grain magazine was raised and illuminated for 2.5 s. Components were presented in a random order, with the restriction that exactly 18 red and green components occurred during the session. As in the concurrent-chains procedure, all nonreinforced responses produced a 0.05-s darkening of the center key.

The multiple schedule differed from the usual arrangement (e.g., Nevin, 1974), in that components were not of fixed duration and always ended with a single reinforcer. This was done so that the multiple schedule would be as similar as possible to the concurrent-chains terminal links.

Response-independent food test sessions. In each condition, test sessions were conducted in

Table 1

Order of the conditions (the same for all subjects) and VI schedules arranged during the left and right terminal links (and multiple-schedule components signaled by same stimuli). All schedule values are in seconds. Shown also are the number of sessions of baseline training given all subjects prior to conducting VT food tests.

Condition	Left terminal link	Right terminal link	Number of baseline sessions
1	VI 16.67	VI 33.33	40
2	VI 33.33	VI 16.67	51
3	VI 7.14	VI 42.86	31
4	VI 42.86	VI 7.14	35
5	VI 12.5	VI 37.5	35
6	VI 37.5	VI 12.5	35
7	VI 3.85	VI 46.15	28
8	VI 46.15	VI 3.85	35

which response-independent food was presented during the ICI of the multiple schedule according to a VT 10-s schedule. Duration of VT reinforcement was the same as that during the multiple schedule (2.5 s), and the ICI did not elapse during VT reinforcement. The VT reinforcement was intended to be a disrupter for responding during the multiple schedule, so that measures of resistance to change in each component could be obtained.

The experiment consisted of eight conditions, which were defined by the VI schedules used for the terminal links and multiple-schedule components. The order of conditions and the number of baseline training sessions preceding testing are given in Table 1 for all subjects. The VI schedule values always summed to 50 s, but the relative immediacies were 2:1, 1:2, 6:1, 1:6, 3:1, 1:3, 12:1, and 1:12. Because the initial-link schedules were the same for all conditions and because interdependent scheduling guaranteed equal exposure to the terminal links, programmed average initial- and terminal-link durations were constant throughout the experiment, which Grace (1994) suggested as a way to minimize temporal context effects on preference.

Baseline training in each condition continued until responding in the concurrent chains and multiple schedule appeared to be stable for all subjects. Then, response-independent food test sessions were conducted. For the first three conditions, there were five single-session tests, each followed by three baseline sessions. The fifth single-session test was followed by five additional baseline sessions and a final contiguous block of five test sessions. Because the data from the five-session block were more orderly, data from the single-session tests are not reported, and single-session tests were no longer conducted after the third condition. For the last two conditions, an additional block of five test sessions was run with the same VT 10-s schedule during the ICI, but responding in the multiple schedules produced keylight offset only (VT+EXT). This final block of test sessions was also preceded by five baseline sessions, and was included to explore the effect of a disrupter of greater magnitude on resistance to change at the most extreme reinforcer ratios.

RESULTS

The primary dependent variables were the response rates during the initial and terminal links of the concurrent chains and those during the components of the multiple schedule. Also recorded were the obtained times until reinforcement in the terminal links and multiple schedule. Response rates averaged over the last five sessions of baseline preceding the block of five VT test sessions, and the blocks of five VT test sessions, are listed in Appendix A for all subjects and conditions.

The introduction of VT food usually produced an immediate decrease in response rate. However, responding then remained roughly constant, for all subjects, during the remaining test sessions in each condition. Accordingly, the response rate averaged over the five test sessions was used for subsequent analyses.

Analysis of Preference Data

Figure 1 shows preference, scaled as the log of the relative initial-link response rate, as a function of the log relative obtained terminal-link reinforcement rate, for all subjects and conditions. Data for all subjects were well described by Equation 4; the average variance accounted for was 91.8%. Sensitivity parameters were reasonably close to 1.0, consistent with previous research on concurrent chains with VI terminal links (Grace, 1994). All subjects showed a bias towards the left initial-link

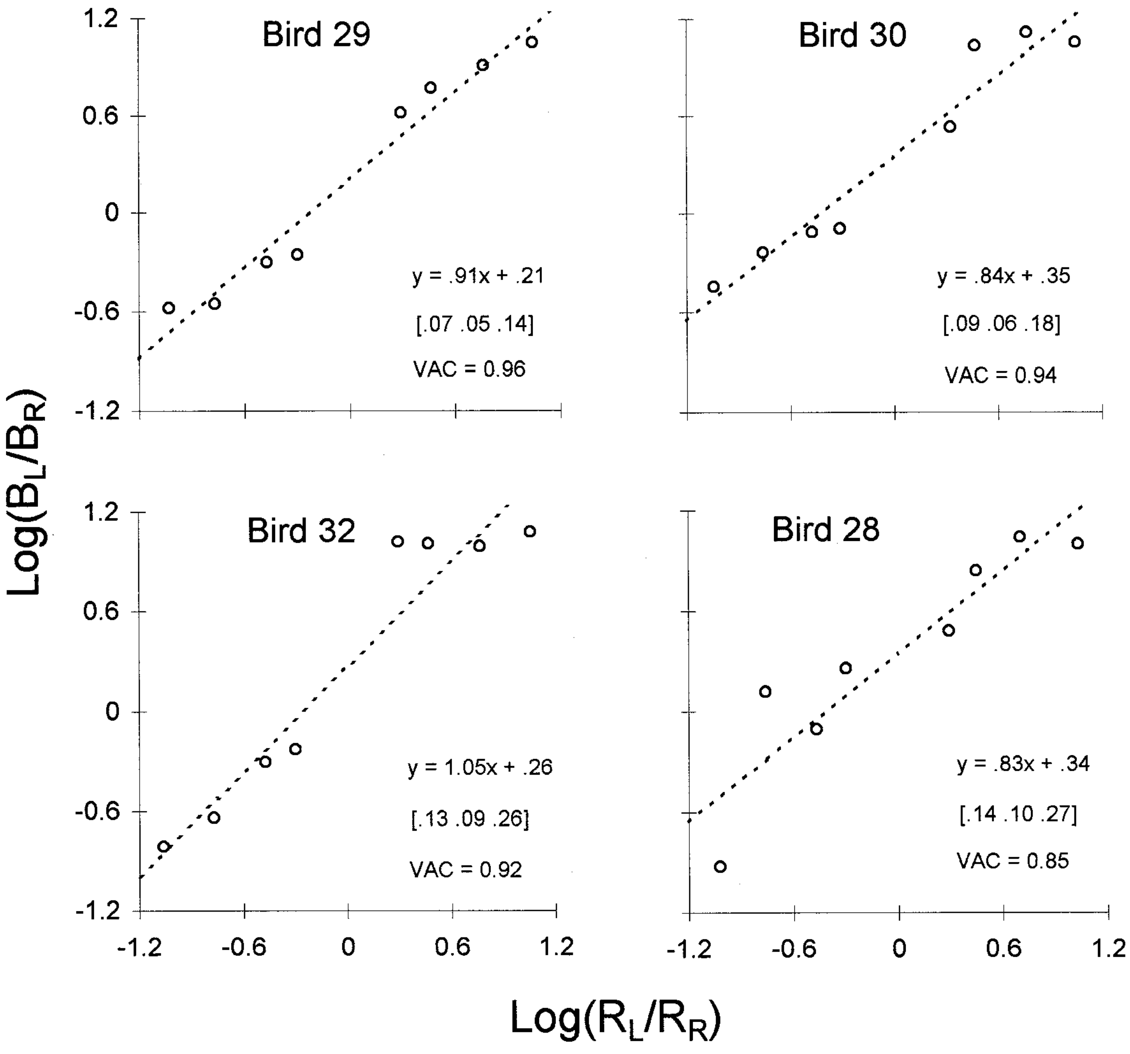

Fig. 1. Preference in concurrent chains as a function of log relative terminal-link reinforcement rate. Dashed lines show the least squares fit of a logarithmic transformation of Equation 4. Also shown are the regression equations with estimated slopes (sensitivity to reinforcement rate) and intercept (log bias), the standard errors of slope, intercept, and prediction (in brackets), and the variance accounted for.

key ($\log b > 0$). Because the colors of the terminal-link stimuli were counterbalanced, this was likely due to position preference. The bias might exemplify hysteresis, resulting from the large total number of sessions given in the first condition (68) in which the left terminal link was preferred.

Analysis of Relative (Between-Component) Resistance-to-Change Data

After baseline training in each condition, response-independent food was presented during the ICI according to a VT 10-s schedule for five consecutive sessions to disrupt multiple-schedule responding. Typically, VT food produces a decrease in response rate, and the amount of decrease in each component, relative to baseline, provides a measure of resistance to change. Previous studies have employed several rates of VT food in separate tests (Nevin, 1974; Nevin et al., 1983); Nevin (1992b), in his reanalysis, used the reciprocal of the slope of the function relating response rate, as a log proportion of baseline, to VT food rate as the measure of resistance to change. For two reasons, this approach was not used here. First, because termination of components was response dependent, if a disrupter reduced response rates to extremely low levels, it would have increased component duration, and the resulting change in reinforcement rate during the test sessions might have reduced responding further, thus confounding the measure of resistance to change. For this reason we also elected not to use extinction or prefeeding tests, which have commonly been employed as disrupters in previous work (e.g., Nevin et al., 1990). Second, the number of sessions required to test three or four different VT rates in each of eight conditions and with baseline training between tests for different rates would have been prohibitively high. We therefore wanted a measure of resistance to change using only a single VT rate, one that would be sensitive enough to yield reliable differences in relative resistance but that would not disrupt responding so much that obtained reinforcement rate would change dramatically.

Appendix B derives the following equation for relative resistance to change as a function of reinforcement rates in the multiple schedule:

$$\log\frac{B_{x1}}{B_{o1}} - \log\frac{B_{x2}}{B_{o2}} = a_{m'}\log\frac{R_1}{R_2} + \log b_m, \quad (6)$$

where B_x and B_o are response rates during VT food test sessions and the preceding baseline, respectively, and R is reinforcement rate. Subscripts 1 and 2 indicate the components of the multiple schedule, $a_{m'}$ is a sensitivity parameter, and log b_m represents color bias. According to Equation 6, relative resistance to change, measured as the difference of log proportion of baseline in the two components, is a linear function of the log ratio of reinforcement rates. There is an apparent inconsistency between Equation 6 and Nevin's (1992b) integrative model, because Equation 6 defines relative resistance as a difference, not a ratio, of within-component measures. However, Appendix B shows that for the range of conditions considered here, the difference and ratio measures are related by a proportionality constant. The advantages of the difference measure are that it can be computed for cases in which responding in one of the components increases under disruption (whereas the ratio measure cannot), and that it is less sensitive than the ratio measure to perturbations in the data when the overall changes in responding are small.

Figure 2 shows that for all subjects, relative resistance to change was reasonably well described as a power function of relative reinforcement rate. However, compared with the preference data (see Figure 1), the regression slopes are much shallower: Relative resistance to change is less sensitive than preference to changes in relative reinforcement rate. This result was expected on the basis of previous research (Grace, 1994; Nevin, 1992b), and is here confirmed in a within-subject test. Specifically, Grace (1994) found that sensivitity to relative reinforcement rate in concurrent chains with VI terminal links averaged 0.90 across a number of studies (the average here was 0.91), whereas Nevin (1992b) found that a sensivity exponent of 0.35 was consistent with the data on resistance to change (the average here was 0.20). The variance accounted for in the resistance data in Figure 2 is considerably less than in the preference data (most likely because the range of the preference data was greater), and, although the standard errors for sensitivity are smaller for the resistance data, as a proportion of the estimates they are larger. This indicates that sensitivity is measured with relatively less accuracy, overall, in the resistance paradigm.

The points marked with open squares in Figure 2 are from the VT+EXT tests in the final two conditions. Because the magnitude of the disrupter was larger, these points were predicted to lie on a steeper line than the other points. This was clearly true only for Bird 30. Future research should investigate whether the predicted relation between relative resistance to change and disrupter magnitude, using the difference measure, is obtained (see Appendix B).

In the introduction, we noted that the correlation of preference and relative resistance to change across different independent variables, coupled with the procedural similarity of concurrent-chains terminal links and multiple schedules (Nevin, 1979), suggested that preference and relative resistance might be independent measures of a unitary construct that reflects the effects of a history of exposure to the conditions of reinforcement cor-

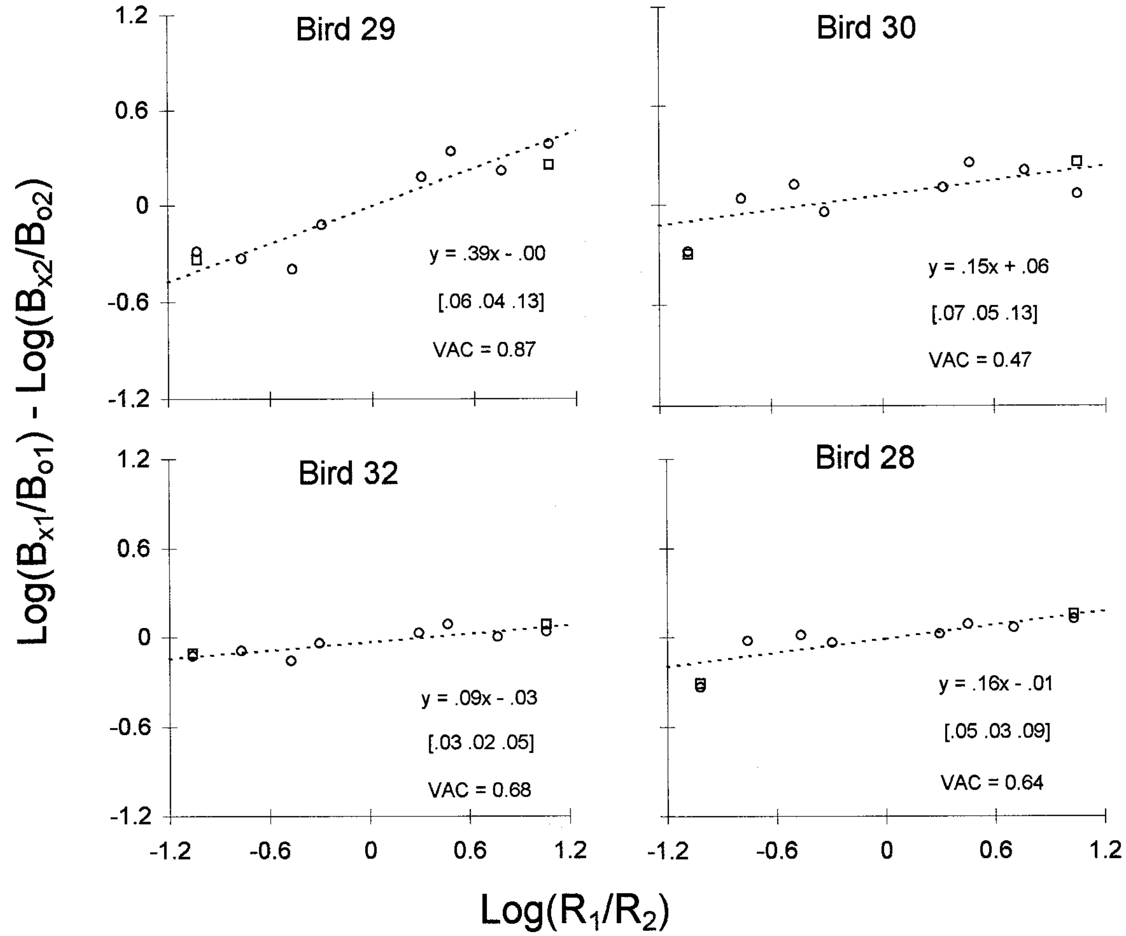

Fig. 2. Relative resistance to change (using the difference measure) in the multiple schedule as a function of log relative reinforcement rate for all subjects. Dashed lines show the least squares fit of Equation 6 to the data marked with open circles (VT tests). Also shown are the regression equations, the standard errors of slope, intercept, and prediction (in brackets), and the variance accounted for. Data points marked by open squares are results from VT+EXT tests.

related with a distinctive stimulus.[1] *Behavioral mass* and *value* are theoretical terms that have been employed in the multiple-schedule and concurrent-chains literatures, respectively, to characterize these effects, and both are given quantitative definition in the models of Nevin (1992b) and Grace (1994).

If resistance to change and preference are independent measures of a unitary construct (designated z) which, in turn, depends on rate of reinforcement, preference and resistance to change should be correlated. Moreover, if that unitary construct also depends on some unknown but systematic factor that modulates the effect of reinforcement rate (i.e., some factor that is not represented in the models of Nevin and Grace), or if that construct varies irregularly for individual subjects in particular conditions (i.e., unsystematic "error" in z), then the residuals from the separate regressions performed on the preference and resistance data in Figures 1 and 2 may also be correlated. These relations may be formalized in general terms as follows.

For the multiple-schedule component and terminal link in condition i,

$$z_i = f_1(R_i) + f_2(X_i) + f_3(E_i), \tag{7}$$

where R_i designates reinforcement rate, X_i is

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[1] Note that our usage of *construct* is similar to Staddon's (1993) definition of a *state variable* in terms of environmental history.

an additional systematic factor, and E_i is an error-like effect in the determination of z_i for an individual subject. These variables are transformed by functions f_1, f_2, and f_3, and are summed to yield z_i. Then, for Schedules 1 and 2 arranged as terminal links and multiple-schedule components in the same condition, preference and relative resistance to change are given by

$$\log\frac{B_1}{B_2} = \log g_p\left(\frac{z_1}{z_2}\right) + \epsilon_p$$

and

$$\log\frac{m_1}{m_2} = \log g_m\left(\frac{z_1}{z_2}\right) + \epsilon_m, \qquad (8)$$

where g_p and g_m are performance functions that relate the constructs z_1 and z_2 to behavior, and ϵ_p and ϵ_m are measurement error associated with preference and relative resistance. (Note that because sensitivity to relative reinforcement rate is greater for preference than resistance, $g_p \neq g_m$.) Even though z_i, the unitary construct measured by preference and resistance, may not be entirely determined by the reinforcer rate correlated with a particular terminal link or component, the within-condition residuals for preference and resistance should be correlated if X_i and E_i are large relative to ϵ_p and ϵ_m. Indeed, such correlations would be evidence in favor of a unitary construct.

Figure 3 shows residuals from the relative resistance-to-change regressions (Figure 2) as a function of the residuals from the preference regressions (Figure 1) from the same condition. There was a significant positive correlation, pooled over subjects, between the preference and resistance residuals, $r = 0.52$, $p < .003$. In addition, all correlations for individual data were positive, $r = 0.65$ (Bird 29), $r = 0.42$ (Bird 30), $r = 0.59$ (Bird 32), $r = 0.76$ (Bird 28), although only that for Bird 28 reached statistical significance, $p < .03$. Overall, this is evidence that preference and relative resistance to change covary, not only in that both are increasing functions of relative reinforcement rate, but that if both are measured independently for the same pair of VI schedules, error with respect to a regression found in one is also likely be found in the other. The correlation of residuals is consistent with the hypothesis that preference and relative resistance to change are measuring the same construct.

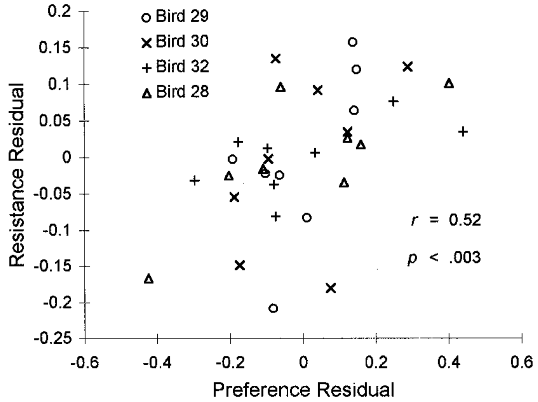

Fig. 3. This figure shows, for all subjects and conditions, the residual from the regression on the resistance-to-change data (Figure 2), as a function of the residual from the regression on the preference data (Figure 1) from the same condition. Data for individual subjects are marked as noted in the legend. Correlations for all subjects were positive; pooled over subjects, the correlation was highly significant. This demonstrates that unsystematic variation in relative resistance and preference was correlated within subjects. See text for more explanation.

An alternative explanation for the positive correlation is whether the preference and resistance residuals showed the same pattern of systematic, rather than unsystematic, deviation from linearity in Figures 1 and 2. Perhaps preference and resistance are not adequately described as power functions of relative reinforcement rate. Then, the residuals might be correlated, but this would imply that nonlinear functions (in logarithmic coordinates) were more appropriate, not necessarily that the error was correlated. However, inspection of Figures 1 and 2 reveals no systematic deviation across subjects. Evidently, Figure 3 shows correlation of error that is unsystematic with respect to relative reinforcement rate, which supports the hypothesis that preference and relative resistance to change are independent measures of a single construct.

A second alternative explanation concerns the possibility that there may have been systematic component order effects in the data. The order of the concurrent chains and multiple components was determined randomly in baseline, but in the test sessions the multiple schedule always occurred second. If preference and the multiple-schedule response rates changed systematically depending on component order, then variation in the composition of the five sessions used for baseline in each condition due to random sampling could have artifactually produced correlation of the preference and resistance residuals. Specifically, it might be anticipated that preference would be more extreme when concurrent chains occupied the second half of the session, because the prior multiple schedule could be viewed as pretraining, with the stimuli presented separately, on the choice discrimination. It also might be predicted that the multiple-schedule response rates would be lower when that component occurred second, because the reinforcers obtained in the concurrent chains could function as prefeeding. If response rate was reduced relatively more in the lean multiple-schedule component than in the rich component, then when relatively more of the five sessions comprising baseline had the component order concurrent chains → multiple schedule, relative resistance to change should be reduced, compared with the case in which fewer of the five sessions had that order, because the attenuation of baseline response rates would be greater in the lean than in the rich multiple-schedule component. Similarly, when more of the five baseline sessions were concurrent chains → multiple schedule, preference would also be reduced. Thus, if these component order effects are present, variation in baseline preference and multiple-schedule response rates due to random sampling of component order might be responsible for the correlation of residuals that are seen in Figure 3.

To determine if component order effects were present in the data, we analyzed the data from the last 10 sessions of baseline training in each condition. These data were separated for each subject into two groups depending on component order. Multiple-schedule response rates were higher when the multiple schedule occurred first in 13 of 16 cases for Bird 29, 15 of 16 cases for Bird 30, 15 of 16 cases for Bird 32, and 10 of 16 cases for Bird 28. This indicates that the concurrent chains may have functioned as a disrupter (i.e., prefeeding) when it was the first component in the session. Next, multiple-schedule response rates were averaged over successive condition reversals, and the response rates when the multiple schedule was second were subtracted from the rates when it was first, and divided by the rates when it was second. For the rich and lean components of the multiple schedules, the proportional differences for each bird, averaged over conditions, were, for Bird 29, .05 and .06; for Bird 30, .29 and .34; for Bird 32, .07 and .25; and for Bird 32, .04 and .04. Increases were relatively greater in the lean component for 3 of the 4 birds. Finally, for the preference data, the log relative initial-link response rate was more extreme when concurrent chains occurred second in eight of eight cases for Bird 29, five of eight cases for Bird 30, seven of eight cases for Bird 32, and seven of eight cases for Bird 28. Therefore, these analyses demonstrate that preference in concurrent chains and response rates in the multiple schedule did vary systematically depending on component order, and that this variation occurred in the manner described in the previous paragraph and thus was potentially responsible for the correlation of residuals in Figure 3.

We performed several additional analyses to determine if these component order effects were sufficient to explain the observed residual correlation. Table 2 shows the results. Using the data from the last 10 sessions as baseline, we replicated the preference (Figure 1), relative resistance (Figure 2), and residual correlation (Figure 3) analyses three different ways, depending on whether baseline was defined as (a) all 10 sessions, (b) only those sessions with component order concurrent chains → multiple schedule, or (c) only those sessions with component order multiple schedule → concurrent chains. Component order effects are evident in Table 2: For all subjects, the slope of the preference regression is greater for those sessions in which concurrent chains occurred second than for those in which it occurred first. Differences in slope for relative resistance were less systematic; only the slopes for Birds 30 and 32 were greater when the multiple schedule occurred first. But most important, for all three definitions of baseline, the residual correlation was significantly positive. Therefore, although the order of components did affect responding in both concurrent chains and the multiple schedule, it cannot explain the correlation of preference and resistance residuals in Figure 3, because this correlation

Table 2

This table shows the regression parameters and variance accounted for when the preference and resistance data were analyzed using three sets of data for baseline: (a) the 10 sessions preceding the resistance tests; (b) only those sessions (of the 10) in which the multiple schedule was the first component; and (c) those sessions in which concurrent chains was the first component. Although component order effects were present—note that the slope (i.e., sensitivity to delay) for preference is greater for mult CC than for CC mult for all subjects—the correlation between preference and resistance residuals was always significantly positive.

		Preference			Resistance			Correlation of preference and resistance residuals
Bird	Source of data	Slope	Intercept	VAC	Slope	Intercept	VAC	(and p values)
29	all 10 sessions	0.90	0.19	.95	0.40	0.01	.89	
	mult CC only	0.98	0.20	.95	0.40	0.01	.88	
	CC mult only	0.81	0.17	.94	0.40	0.01	.88	
30	all 10 sessions	0.74	0.29	.93	0.13	0.05	.43	
	mult CC only	0.75	0.25	.90	0.14	0.05	.45	
	CC mult only	0.74	0.32	.92	0.12	0.05	.41	
32	all 10 sessions	1.00	0.26	.91	0.10	−0.03	.72	
	mult CC only	1.11	0.26	.90	0.14	−0.02	.83	
	CC mult only	0.91	0.27	.91	0.05	−0.02	.38	
28	all 10 sessions	0.73	0.31	.88	0.14	−0.01	.64	
	mult CC only	0.89	0.39	.87	0.14	−0.01	.65	
	CC mult only	0.61	0.27	.78	0.14	−0.01	.61	
All	all 10 sessions							.50 ($p < .004$)
	mult CC only							.53 ($p < .002$)
	CC mult only							.44 ($p < .013$)

was obtained regardless of the order of components in baseline.

Nevin's (1992b) model for behavioral momentum and Grace's (1994) model for concurrent chains define relative resistance to change and preference, respectively, as power functions of relative reinforcement rate. As shown above, this implies that preference and relative resistance should be related by a power function with an exponent that is the ratio of the exponents relating each to relative reinforcement rate (Equation 5). Figure 4 shows relative resistance to change as a function of preference in the same condition, for all subjects. The dashed lines were obtained by fitting a logarithmic transformation of Equation 5 with a structural relations procedure (Davison & McCarthy, 1988, p. 73). Although it is difficult to make a direct comparison because of the different ways in which the functions were fitted, it is interesting to note that the variances accounted for are greater for all subjects in Figure 4 than for the corresponding fits in Figure 2 when the resistance data were regressed on relative reinforcement rate. This difference is a byproduct of the correlation of preference and resistance residuals shown in Figure 3.

Analysis of Absolute (Within-Component) Resistance-to-Change and Response-Rate Data

All previous research on resistance to change has involved comparisons between components of multiple schedules. Whether these comparisons are made within a single experimental condition or between different conditions, it is an analysis of relative resistance to change (Nevin, 1992b). In Appendix B, we show that it is possible to examine absolute resistance data (i.e., within-component comparisons) meaningfully, if behavioral mass is a specified function of reinforcement rate and if the effectiveness of different disrupters can be scaled in units of the reinforcer. These assumptions yield the following expression that describes resistance to change within components:

$$\log\frac{B_x}{B_o} = \frac{-x}{R^{a_m}} + p, \qquad (9)$$

where x is the magnitude of the disrupter ($x > 0$) and p is a dimensionless constant that allows for the possibility that response rate might paradoxically *increase* for disrupters of low or moderate intensity when reinforce-

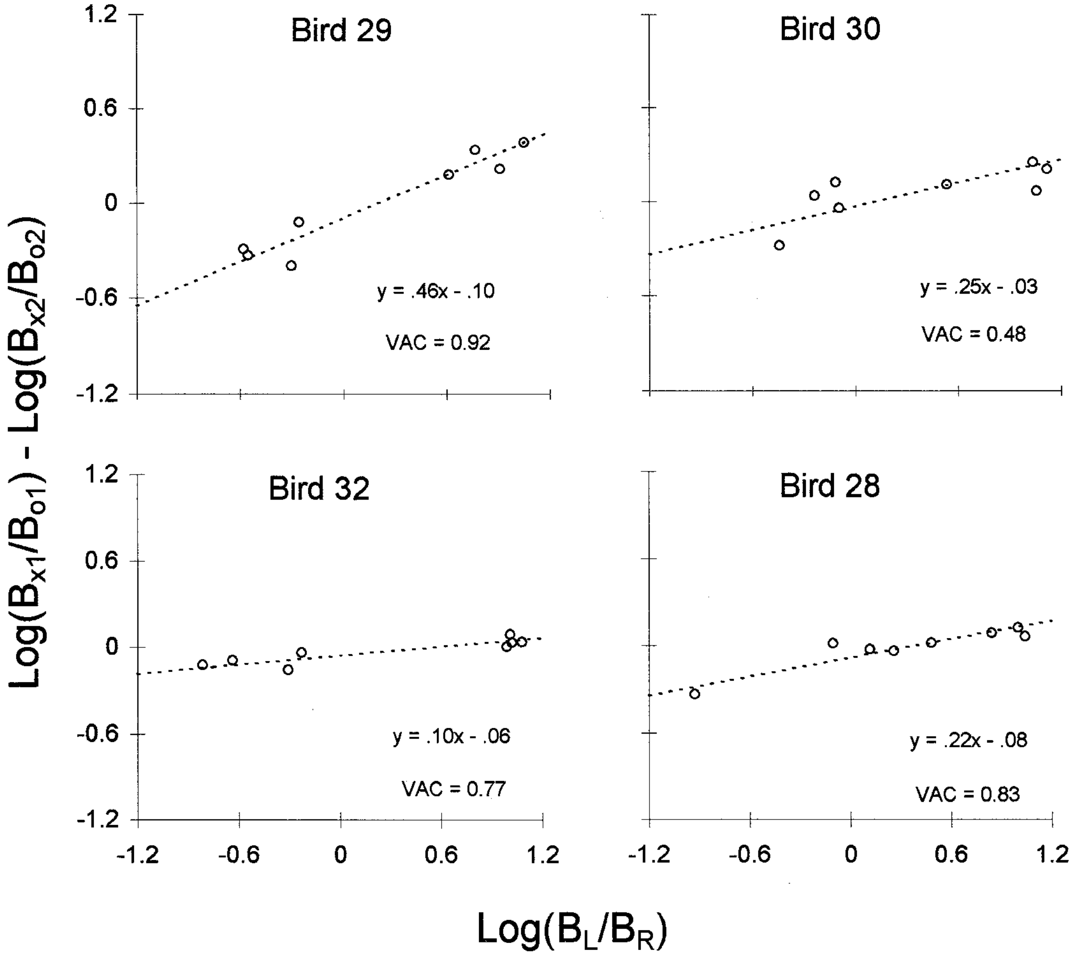

Fig. 4. Relative resistance to change (using the difference measure) in the multiple schedule as a function of concurrent-chains preference from the same condition. Dashed lines show the structural relations fit of a logarithmic transformation of Equation 5 to the data. Also shown are the parameters of the equation and the variance accounted for.

ment rate is high. This increase might occur if baseline response rates are underestimated. Baum (1993) has found that the response-rate function for VI schedules is nonmonotonic, because postreinforcement pauses represent a greater proportion of the programmed interreinforcer intervals as reinforcement rate increases (see also Killeen, 1994).

The within-component resistance-to-change data for each subject are shown in Figure 5. Equation 9 was fitted to these data, assuming different values of the disrupter (x) for the VT and VT+EXT data. Because only 2 subjects (Birds 29 and 28) consistently produced increases in response rate (see below), p was estimated only for these birds (and was set equal to zero for the others). The fits of Equation 9 were only minimally adequate, accounting for an average of 75.5% of the variance overall. However, it should be noted that Equation 9 would be better suited for a data set in which x was varied parametrically in addition to the variation in reinforcement rate.

Several aspects of Figure 5 are worth noting. First, for all subjects and as expected, resistance to change ($\log B_x/B_o$) was an increasing function of reinforcement rate. This demonstrates that our within-session procedure gives results that are in ordinal agreement with those from previous research (e.g., Nevin, 1974; Nevin et al., 1983). Second,

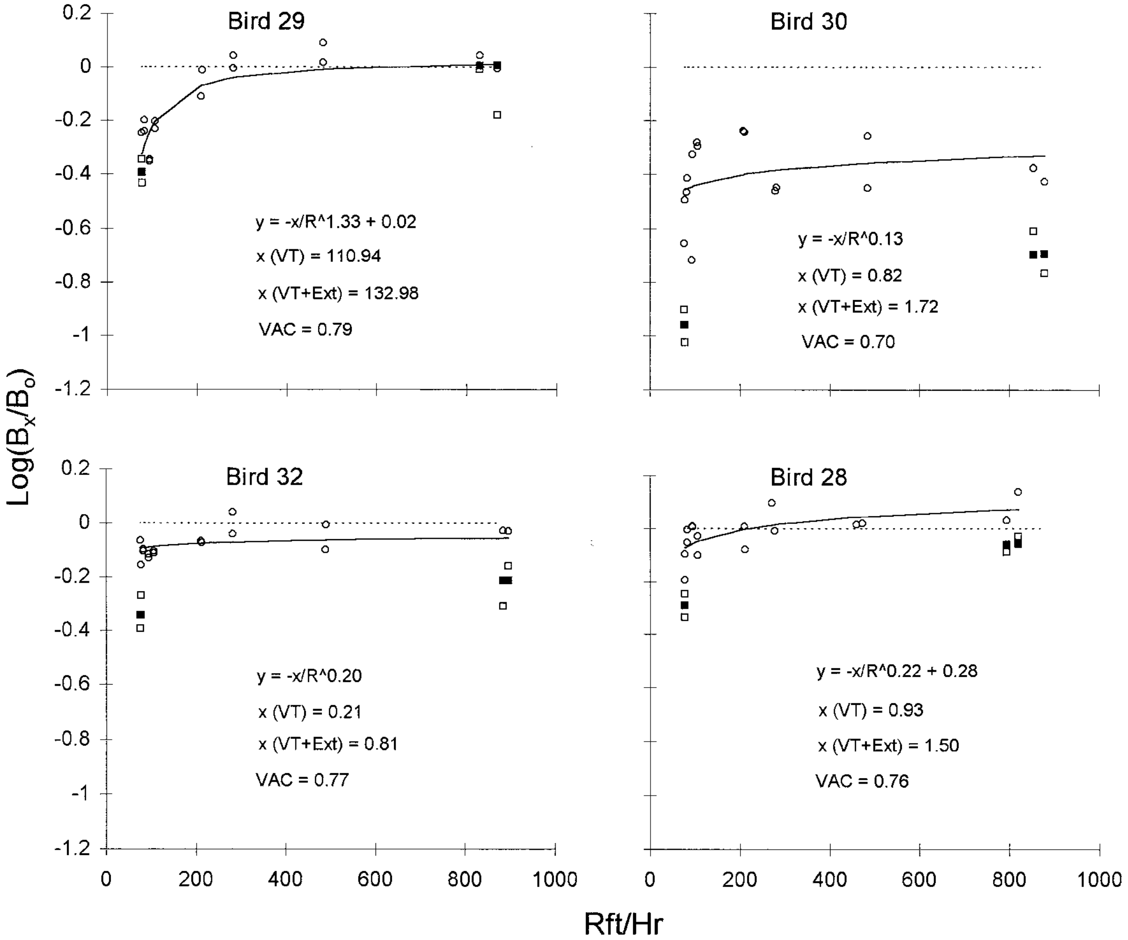

Fig. 5. Within-component resistance-to-change data as a function of reinforcement rate. Data points marked by open circles are from the VT tests; those marked by open squares are from the VT+EXT tests. Dashed lines indicate no change from baseline in responding during test (i.e., $B_x = B_o$). The solid lines and filled squares represent the best fits of Equation 9 to the VT and VT+EXT data, respectively (assuming different values of x). The variance accounted for and estimated parameter values are also listed. Note that because x and a_m scale reinforcer and disrupter effectiveness jointly in units of reinforcers per unit time, between-subject variability in estimates of x corresponds to variability in estimates of a_m.

there were individual differences in absolute and relative resistance to change. Response rates of Bird 30 consistently showed the greatest relative decrement of all subjects in the test sessions (i.e., least absolute resistance to change). However, the slope of the best fitting Equation 9 was steepest for Bird 29, indicating the greatest changes in relative resistance for this bird (also confirmed by the regression slopes in Figure 2). Third, the VT+EXT test produced greater decrements in response rate, as expected, for all subjects in the last two conditions. This makes sense, because here the food presentations for responding in the components of the multiple schedule were eliminated, in addition to the VT food being delivered during the ICI. The greater magnitude of this disrupter is reflected in the fact that estimated values of x were greater for VT+EXT than for VT for all subjects. Finally, the increases in response rate, relative to baseline, for Birds 29 and 28 were systematic. Increases generally occurred only for high reinforcement rates, so baseline response rates may have been underestimated for these conditions. Although Bird 28's maximum response rate was, surprisingly, obtained at low reinforcement rates (see be-

Table 3

Estimated parameters (k and R_e) and variance accounted for (VAC) by Herrnstein's hyperbola, as fitted separately to the multiple-schedule and terminal-link response rate data for each subject. Response rates were averaged over successive conditions to give a total of eight data points per subject. Also shown are overall values of resistance to change, log (B_x/B_o), averaged over 16 determinations per subject.

	Multiple schedule			Terminal links			
Bird	k	R_e	VAC	k	R_e	VAC	Average resistance
29	103.08	25.26	.81	95.88	17.52	.69	−0.13
30	170.80	102.20	.88	135.33	57.29	.82	−0.41
32	169.78	54.07	.88	155.83	32.99	.83	−0.07
28	80.99	−9.22	.06	72.49	−17.98	.26	−0.01

low), there was no downturn in responding for Bird 29 at high reinforcement rates. This suggests that the increases in response rate under disruption cannot, in general, be attributed to a nonmonotonic response-rate function.

To determine whether individual differences in resistance to change might be correlated with differences in baseline responding during the multiple schedule, response rates, averaged over successive-condition reversals, were analyzed with Herrnstein's (1970) hyperbola. For sake of comparison, response rates in the terminal links were similarly analyzed. The multiple-schedule equation was used, but in all cases the best fitting value of m was zero (i.e., no component interaction), which means that the single-schedule equation is appropriate. Consequently, Table 3 lists, for all subjects, the values of k and R_e that maximized the variance accounted for by Herrnstein's single-schedule equation in the response-rate data. Because components terminated after a single reinforcer, it should be acknowledged that this is perhaps not an ideal data set for estimating parameters for Herrnstein's equation. Nevertheless, data for 3 of the 4 subjects (the exception being Bird 28) were reasonably well described by the hyperbola. Maximum response rates for Bird 28 were achieved with low reinforcement rates, which produced negative estimates for R_e. Although it is unclear why this occurred only for Bird 28, one possibility is a latency to begin responding at the start of a terminal link or a component of the multiple schedule, which, if constant, would have resulted in a greater proportion of the timed interval elapsing, without any responses, at high reinforcement rates.

Table 3 also lists the resistance to change for each subject in the VT food tests, averaged over 16 separate determinations. Of interest is whether differences in overall resistance to change are predicted by differences in R_e. An analysis in terms of Herrnstein's (1970) hyperbola implies that responding should be more readily disrupted by alternative reinforcement if R_e is low than if R_e is high. This is because VT food decreases response rate through increasing R_e, and a given increment in R_e is relatively less effective if R_e is high than if R_e is low. (Note that we are assuming that subjects' sensitivities to VT food are equal.) However, Table 3 shows that, if anything, the opposite was obtained: Bird 30, whose responding was disrupted the most, had the highest estimated R_e, whereas Bird 28, whose responding was disrupted the least, had the lowest R_e. This result is consistent with other results showning that Herrnstein's hyperbola does not give a comprehensive account of resistance to change (Nevin, 1992a; Nevin et al., 1990).

It is also clear from Table 3 that the estimates of k and R_e were lower for responding in the terminal links than in the multiple schedule for all subjects. This reflects the fact that at low reinforcement rates, there were no systematic differences between responding in the terminal links and in the multiple schedule, but at high reinforcement rates, multiple-schedule response rates were consistently higher. Why this difference occurred is unclear. It might have been expected that terminal-link response rates would be higher, given that initial-link keylight offset was a reliable signal of the beginning of a terminal link, whereas the multiple-schedule components began after a 30-s ICI. The latency to begin responding therefore should have been longer for the multiple schedule.

DISCUSSION

Nevin (1979) noted that the variables that increase resistance of responding to disruption in multiple schedules also increase preference for a terminal link in concurrent chains. Recent quantitative models for resistance to change (Nevin, 1992b) and preference (Grace, 1994) carry this idea one step further, by defining both variables as power functions of relative reinforcement rate. To explore the relationship between preference and resistance to change empirically, we introduced a new procedure that arranged concurrent chains in one half of a session and a multiple schedule in the other half. The crucial aspect of the procedure was that the concurrent-chains terminal links were identical, in terms of discriminative stimuli and reinforcement schedules, to the multiple-schedule components. This allowed measures of preference and resistance to change to be obtained for the same schedules, within subjects, in each of eight conditions. Both preference and relative resistance to change were well described as power functions of relative reinforcement rate. The exponent for preference was larger, consistent with findings from previous studies, indicating that preference is more sensitive to changes in relative reinforcement rate. These consistencies demonstrate the utility of our within-session procedure as a technique for obtaining independent measures of preference and resistance to change.

Behavioral mass and *conditioned reinforcement value* are theoretical constructs that have been employed in the resistance-to-change and preference literatures, respectively, to represent the effects of reinforcement in the presence of a distinctive stimulus situation on behavior in a different situation. The different situation is the presence of a disrupter in a multiple schedule or the initial links of concurrent chains. Expressed in other terms, mass and value may be said to represent the learning that has occurred regarding reinforcement in the presence of a stimulus, which then transfers to the different situation. As such, resistance to change and preference may be independent measures of a single construct, in which case our within-session procedure can be construed as providing converging operations to measure that construct (Garner, Hake, & Eriksen, 1956).

If preference and relative resistance to change are different expressions of the same learning, and if learning is a function of reinforcement rate and additional systematic or unsystematic factors that are large relative to measurement error (see Equations 7 and 8), then the residuals from separate regressions performed on the preference and resistance data should be correlated. Pooled over subjects, residuals from the regressions in Figures 1 and 2 were positively correlated, $r = 0.52$, $p < .003$ (see Figure 3). This correlation is strong evidence in favor of the validity of a construct—known variously as *response strength, behavioral mass,* or *value*—that quantifies the learning about the conditions of reinforcement signaled by a particular stimulus as a power function of reinforcement rate in the presence of that stimulus.

Quantitative Analyses of Resistance to Change

Our experiment represents a further step in the maturation of research on resistance to change, bringing it to a level of quantification comparable to research on preference. Early studies demonstrated ordinal agreement across different types of disrupters: Whether extinction, satiation, or response-independent food delivered between components was used as a disrupter, responding in the multiple-schedule component with the greater frequency, immediacy, or magnitude of reinforcement declined less, relative to baseline (Nevin, 1974). Nevin argued that the consistency of such results implied that response strength should be measured as resistance to change rather than response rate (cf. Herrnstein, 1970; Skinner, 1938). Nevin et al. (1983) conducted the first parametric study on resistance to change and found that relative resistance to change was a power function of relative reinforcement rate (see their Figure 6). Nevin et al. also proposed behavioral momentum theory as a framework for studying resistance to change, identifying resistance to change and response rate as independent dimensions of operant behavior that are analogous to the mass and velocity of a moving object. Subsequent research confirmed their independence by showing that resistance to change was determined primarily by Pavlovian stimulus–reinforcer contingencies, whereas response rate was controlled by operant response–reinforcer contingencies (Nevin, 1984, 1992a; Nevin et al., 1987, 1990). Nevin (1992b) proposed an integrative model for resistance to change, employing Gibbon and Balsam's (1981) contingency ratio to quantify stimulus–reinforcer relations, that gave a reasonably accurate description of the group-mean data from all relevant previous studies conducted in his laboratory. Here, we have explored the relation between resistance to change and preference both analytically and experimentally, applied models to individual data, and obtained evidence that preference and resistance to change are measures of a single construct.

Because in most previous studies resistance data have been analyzed at the ordinal level, whether responding relative to baseline as a function of the disrupter was scaled linearly or logarithmically was largely irrelevant; what mattered was the ordering of the slopes (cf. Harper & McLean, 1992; Nevin et al., 1990). With increasing quantification, however, measurement issues have become paramount. To make meaningful comparisons with preference data, it is necessary to have a measure of relative resistance that (a) has the same scale properties as the measure used for preference (i.e., a log-interval scale) and (b) is theoretically justified in the context of an overall account of responding under disruption, such as Nevin et al.'s (1983) behavioral momentum theory. Although our difference measure of relative resistance (Equation 6) might be justified here purely on pragmatic grounds, it is not equivalent to the ratio measure that Nevin has previously used. According to momentum theory, it is the ratio measure that equals the ratio of behavioral masses (Equation 13). To avoid inconsistency with prior work, therefore, we have shown that for the schedule values used here, momentum theory predicts that the difference measure should be related to the ratio measure by a proportionality constant, to a very close approximation (see Appendix B).

Previous research has emphasized analysis of *relative* resistance to change (i.e., between-component comparisons). Nevin et al. (1983) reasoned that, because disrupters are measured in different physical units (e.g., sessions of extinction, rate of VT food) and because behavioral mass is derived from the functional relation between response rate as a proportion of baseline and disrupter magnitude, there cannot be an absolute scale of behavioral mass that is valid across different disrupters. However, in Figure 5 we were able to analyze absolute resistance data (i.e., within-component comparisons), by assuming that the effectiveness of a disrupter can be scaled in units of the reinforcer (see Equation 9). This is similar to Herrnstein's (1970) argument that extraneous reinforcers (R_e) could be measured in the same units as the arranged reinforcer. If data from different disrupters can be made to converge onto a single function, perhaps through use of techniques such as nonmetric scaling (Shepard, 1965), it may yet be possible to derive a scale of behavioral mass that is valid across disrupters.

An unexpected result was that response rate sometimes increased rather than decreased during the VT food tests. Because these increases usually occurred in components with high reinforcement rates for Birds 29 and 28 (see Figure 5), there is an implication that they were systematic. In fact, examination of data from other studies that have employed different rates or durations of VT food as disrupters indicates that increases in response rate, when obtained, tend to occur in the richer component and for relatively weak disrupter values (see Harper, 1996, Figure 2; McLean & Blampied, 1995, Figure 5; Nevin et al., 1983, Figure 3). If response rate is a nonmontonic function of reinforcement rate (Baum, 1993; Killeen, 1994) and if the disrupter can be characterized as decreasing the effective reinforcement that maintains the response, then increases like those obtained here could result. However, another possibility is measurement error: When response strength is high and the disrupter is weak, fluctuation in response rate is more likely to produce increases above baseline.

Generality of the Relationship Between Preference and Resistance to Change

We have shown that measures of preference and relative resistance to change are correlated, within subjects, when the component schedules are VIs that terminate after a single reinforcer has been delivered. But just how general is this finding? It is important for future research to test, using a similar within-subject procedure, other variables that affect preference and resistance to change, such as reinforcement parameters (e.g., magnitude or probability; Harper & McLean, 1992; Spetch & Dunn, 1987), fixed versus variable schedules (Grace, 1996; Mandell, 1980; Mellon & Shull, 1986), and response-rate requirements (e.g., preference for DRL over DRH; Fantino, 1968; Lattal, 1989). In addition, it will be important to determine whether the same correlation is obtained when components are of constant duration, and more (or less) than one reinforcer may be earned during a component. This is the way that multiple schedules typically have been arranged (e.g., Nevin, 1974), but this procedure has rarely been used for terminal links in concurrent chains (for exceptions, see Alsop & Davison, 1986; Moore, 1984). The advantage of constant-duration components is that responding can be reduced to zero during disrupter tests with no effect on component duration, so resistance to change can be measured as it has been in previous studies (i.e., as the inverse of the rate of decrease of responding under disruption).

In conclusion, we have shown that the correlation between preference and resistance to change, first noted in a comparison across experiments by Nevin (1979), is obtained within conditions and within subjects. Both preference and relative resistance were well described by power functions of relative reinforcement rate, as expected on the basis of previous research. Importantly, the residuals from these functions showed a substantial positive correlation. The implication is that preference and resistance to change may be independent measures of a single construct, which can be described as the learning that occurs regarding the conditions of reinforcement in a distinctive stimulus situation. Our procedure, which arranged concurrent chains in one half of a session and multiple schedules in the other half, provides converging operations to measure that learning. It should prove to be useful in future research that explores the generality of the relationship between preference and relative resistance to change.

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APPENDIX A

Shown are the VI schedules that served as the terminal links in concurrent chains and in the multiple schedule, for all subjects and conditions. Schedule values are given in seconds. Also listed are the initial- and terminal-link response rates in concurrent chains and the response rates during the multiple schedule (averaged over the last five sessions of baseline) and the response rates in the multiple schedule when response-independent food was delivered between components according to a VT schedule. All response rates are given in responses per minute.

				Response rates							
	Con-di-tion	VI schedule		Concurrent chains				Multiple schedule			
Bird		Left	Right	Init L	Init R	Term L	Term R	Mult L	Mult R	VT L	VT R
29	1	16.67	33.33	39.66	9.62	82.04	93.21	84.98	94.04	82.81	60.74
	2	33.33	16.67	25.45	45.86	72.33	97.23	72.16	102.63	42.41	79.74
	3	7.14	42.86	49.11	6.05	92.10	78.61	95.69	72.80	99.65	46.13
	4	42.86	7.14	15.79	56.61	61.93	97.29	70.03	100.75	40.29	123.90
	5	12.50	37.50	24.34	4.14	88.37	91.07	97.57	92.44	96.47	41.77
	6	37.50	12.50	13.96	27.94	78.21	93.80	84.23	97.57	37.37	107.68
	7	3.85	46.15	34.82	3.09	96.45	96.16	105.78	93.03	103.92	37.44
	8	46.15	3.85	7.83	29.80	68.30	84.46	61.94	86.55	35.19	95.45
30	1	16.67	33.33	35.46	10.37	100.65	95.52	114.80	100.42	65.56	44.96
	2	33.33	16.67	9.36	11.59	57.97	103.88	65.21	82.84	34.16	47.86
	3	7.14	42.86	63.50	4.82	119.72	88.97	106.12	61.70	58.66	21.10
	4	42.86	7.14	17.96	31.06	79.30	127.36	81.68	175.88	31.48	62.28
	5	12.50	37.50	25.07	2.31	115.22	81.98	112.90	68.38	38.85	13.14
	6	37.50	12.50	11.27	14.64	96.91	145.03	83.38	151.53	39.39	53.93
	7	3.85	46.15	29.42	2.57	111.91	81.90	140.93	96.64	52.58	30.93
	8	46.15	3.85	3.91	10.85	64.34	122.05	95.09	171.36	21.13	72.17
32	1	16.67	33.33	80.27	7.70	133.70	104.63	124.04	95.92	105.30	75.60
	2	33.33	16.67	30.05	50.68	127.51	149.00	112.50	144.65	87.00	122.06
	3	7.14	42.86	73.76	7.55	151.38	101.46	152.53	95.87	121.72	75.74
	4	42.86	7.14	18.23	79.31	111.96	149.91	109.55	177.79	87.54	175.17
	5	12.50	37.50	43.08	4.23	126.86	112.35	134.79	113.65	122.92	84.30
	6	37.50	12.50	12.09	24.45	116.39	125.67	109.84	122.65	83.97	134.57
	7	3.85	46.15	34.94	2.92	146.18	111.24	140.62	101.89	131.82	87.66
	8	46.15	3.85	3.64	23.73	126.21	159.23	115.30	179.18	80.90	167.50
28	1	16.67	33.33	48.69	16.12	94.07	112.50	120.57	116.77	100.47	92.46
	2	33.33	16.67	35.98	19.91	84.20	101.08	85.83	90.95	80.73	92.98
	3	7.14	42.86	62.17	5.66	54.41	84.28	60.90	72.84	63.12	64.77
	4	42.86	7.14	34.23	26.21	75.34	76.00	77.22	81.92	76.46	85.81
	5	12.50	37.50	24.62	3.55	52.38	75.67	59.26	65.92	74.24	67.26
	6	37.50	12.50	13.81	17.52	76.78	77.02	82.01	81.00	83.36	79.39
	7	3.85	46.15	29.22	2.93	87.51	110.17	97.32	105.17	104.58	84.38
	8	46.15	3.85	2.82	23.80	103.62	74.58	110.71	80.48	70.94	110.99

APPENDIX B: MEASURING RESISTANCE TO CHANGE WITHIN AND BETWEEN COMPONENTS

Resistance to change has typically been measured as the log proportion of baseline response rate that is obtained when a disrupter, such as extinction or response-independent food, is applied to an established operant response; more formally, $\log(B_x/B_o)$, where B_x is the response rate under disruption and B_o is the rate during the preceding baseline. According to Nevin's (1992b) behavioral momentum theory, this measure is directly (and negatively) related to the magnitude of the imposed force (i.e., disrupter) and inversely related to behavioral mass, a theoretical construct that represents response strength:

$$\log\frac{B_x}{B_o} = \frac{-x}{m}, \qquad (10)$$

where x is the magnitude of the disrupter and m is behavioral mass. Nevin (1992b; see also Nevin et al., 1983) has argued that because the left side of Equation 10 is dimensionless, there cannot be a scale of behavioral mass that is valid across different disrupters, because different disrupters are measured in different physical units. For this reason, he has advocated analyzing relative resistance to change. A two-component multiple schedule is ideal for such an analysis, because a disrupter can be applied equally to responding in both components. The ratio of the resistance-to-change measures in each component then gives a measure of relative (i.e., between-components) behavioral mass, because the disrupter cancels out.

However, a within-component scale of mass, valid across different disrupters, is possible if two assumptions are made. First, we must define behavioral mass as a specific function of reinforcement rate. This will determine the units for behavioral mass. And second, we assume that the effectiveness of a disrupter can be measured in the same units as the reinforcer. Note that this is similar to Herrnstein's (1970) definition of extraneous reinforcers. If both of these assumptions are made, the right side of Equation 10 becomes dimensionless.

Specifically, we will define mass to be a power function of reinforcement rate; this is consistent with previous work on resistance to change and with the definition of terminal-link value in concurrent chains employed by the contextual choice model (Grace, 1994). And because imposition of VT food sometimes can paradoxically produce an *increase* in responding, particularly for high baseline reinforcement rates, we will include an additive dimensionless constant. This constant allows for the possibility that because the function relating response rate to reinforcement rate in VI schedules is nonmonotonic, due to interference effects such as postreinforcement pauses (Baum, 1993; Killeen, 1994), for the purposes of assessing resistance to change baseline response rates may be underestimated at high reinforcement rates. All of these assumptions give an equation for the resistance to change of responding in an individual component:

$$\log\frac{B_x}{B_o} = \frac{-x}{R^{a_m}} + p \qquad (\text{for } x > 0), \qquad (11)$$

where a_m is the exponent of the power function relating mass to reinforcement rate (R), and p is the additive constant. Figure 5 shows the fits of Equation 11 to the within-component resistance to change data for individual subjects. Although these data are more variable than the between-component data (Figure 2), the overall trend is adequately captured.

The primary purpose of the experiment was to obtain measures of relative resistance to change and compare them with preference for the same schedules in concurrent chains. As a measure of relative resistance, Nevin (1992b) has employed the ratio of the reciprocals of the slopes of the functions relating response rate to disrupter magnitude. From Equation 10:

$$\log\frac{B_{x2}}{B_{o2}} \bigg/ \log\frac{B_{x1}}{B_{o1}} = \frac{-x_2}{m_2} \bigg/ \frac{-x_1}{m_1}. \qquad (12)$$

If we assume that the disrupter is applied equally to both components ($x_1 = x_2$) and that mass is a power function of reinforcement rate, then Equation 12 simplifies to:

$$\log\frac{B_{x2}}{B_{o2}} \bigg/ \log\frac{B_{x1}}{B_{o1}} = \frac{1}{m_2} \bigg/ \frac{1}{m_1} = \left(\frac{R_1}{R_2}\right)^{a_m}. \qquad (13)$$

(Note that we are also assuming that $p = 0$.) Equation 13 states that the ratio of resistance-to-change measures taken from individual components should equal the ratio of behavioral masses for responding in those components. Although this ratio is the measure of relative resistance most consistent with Nevin's previous work, we did not use it here for two reasons. First, Equation 13 cannot be computed when responding in one component increases under disruption (as demonstrated by Birds 29 and 28 in Figure 2). Second, the ratio measure is extremely sensitive to small perturbations in within-component resistances when the overall change in responding is small. Recall that we did not want to reduce response rates so much that the data would be confounded by a substantial decrease in reinforcement rate because of increased component duration. For these reasons, we used a difference measure for relative resistance:

$$\log\frac{B_{x1}}{B_{o1}} - \log\frac{B_{x2}}{B_{o2}} = x\left(\frac{1}{m_2} - \frac{1}{m_1}\right). \qquad (14)$$

According to Equation 14, the difference between the within-component measures of resistance to change will be the product of the disrupter magnitude and the difference between the reciprocals of the behavioral masses. The advantage of the difference measure is that it can be computed when responding increases in one component. Unlike the ratio measure, however, it is not invariant with respect to disrupter magnitude. But it is important to note that when both can be computed, the difference and ratio measures are ordinally equivalent.

We will now show that for the present experiment, the difference and ratio measures are related, to a very close approximation, by a proportionality constant. Recall that to control for temporal context, the sum of reinforcement immediacies for the two components was kept constant across all conditions, while their ratio varied. Specifically,

$$\frac{1}{R_1} + \frac{1}{R_2} = t, \qquad (15)$$

where t is the overall average reinforcement immediacy (units of seconds per reinforcement). This constancy implies that R_1 and R_2 are not independent, so that R_2 may be expressed in terms of R_1:

$$R_2 = \frac{R_1}{tR_1 - 1}. \qquad (16)$$

We can substitute Equation 16 into the difference measure for relative resistance (Equation 14), again assuming that mass is a power function of reinforcement rate. Algebraic simplification yields

$$\log\frac{B_{x1}}{B_{o1}} - \log\frac{B_{x2}}{B_{o2}} = x\left[\left(t - \frac{1}{R_1}\right)^{a_m} - \left(\frac{1}{R_1}\right)^{a_m}\right]. \qquad (17)$$

We are interested in exploring the relationship between Equation 17 and the ratio measure of relative resistance (Equation 13). To apply the constraint of constant average reinforcement immediacy to the ratio measure and obtain an expression suitable for comparison with Equation 17, we substitute Equation 16 into Equation 13 and take logs of both sides. After simplification,

$$\log\left[\log\frac{B_{x2}}{B_{o2}}\bigg/\log\frac{B_{x1}}{B_{o1}}\right] = a_m\log(tR_1 - 1). \qquad (18)$$

Figure 6 shows a plot of the right side of Equation 18 versus the right side of Equation 17, at three different values of a_m and for a wide range of R_1/R_2 ratios. As in the present experiment, $1/R_1 + 1/R_2 = 50$ seconds per reinforcement, and without loss of generality, x in Equation 17 was set equal to 1 and was moved to the left side of the equation. Although the relationship between the ratio and difference measures is sigmoidal over the full range of R_1/R_2 ratios, for the range in the present experiment and for each value of a_m the difference measure is proportional to the ratio measure, to a very close approximation. R^2 values for linear regressions performed on these data were 1.0 ($a_m = 0.1$), .997 ($a_m = 0.3$), and .994 ($a_m = 0.5$). The implication is that for the conditions in our experiment, the difference and ratio measures of relative resistance are related by a multiplicative constant. Therefore we may write

$$\log\frac{B_{x1}}{B_{o1}} - \log\frac{B_{x2}}{B_{o2}} = a_{m'}\log\frac{R_1}{R_2}, \qquad (19)$$

where $a_{m'} = sxa_m$, s is the slope of the appropriate function in Figure 6 (based on the value of a_m), and x is disrupter magnitude (as-

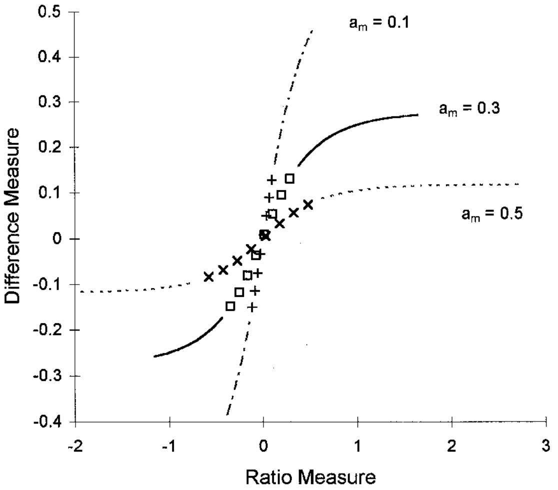

Fig. 6. This figure shows the relationship between relative resistance to change using the difference measure and relative resistance to change using the ratio measure that is predicted by Nevin's behavioral momentum theory. There are functions for three different values of a_m. Data points marked by crosses ($a_m = 0.1$), squares ($a_m = 0.3$) and x's ($a_m = 0.5$) correspond approximately to the range of relative reinforcement rates employed in the present experiment. In this range, to a very close approximation the difference measure is related to the ratio measure by a proportionality constant.

sumed to equal 1 in Figure 6). Thus, increases in disrupter magnitude should make relative resistance, using the difference measure, more sensitive to relative reinforcement; however, this prediction was not fully supported by the VT+EXT data in the final two conditions. (Note that $a_{m'}$ is dimensionless, because s has units of seconds per reinforcement and x has units of reinforcements per second.)

The proportionality demonstrated in Figure 6 between the ratio and difference measures implies that the within-subject correlation of residuals (Figure 3) would also have been obtained if the ratio measure had been used. Therefore, although we did not use the same measure of relative resistance, our results are consistent with Nevin's previous work (e.g., Nevin 1992b). For reasons discussed above (e.g., the increase in response rate under disruption in some cases), the ratio measure could not be used with the present data. Future research should explore the relationship between preference and relative resistance using the ratio measure. For this, a concurrent-chains procedure with constant-duration terminal links seems ideal, because responding can then be reduced to zero with no effect on component duration.