Intertrial Interval and Sequential Effects in Magnitude Scaling

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The intertrial interval (ITI) was varied within subjects in magnitude estimation and cross-modality matching experiments. Fits of a recently proposed time series regression model show that the influence of the previous stimulus intensity on the current response decreases when the ITI is increased. The results can be interpreted as showing that an assimilative or additive perceptual or memory effect decreases with an increase in ITI. Fits of an earlier model, on the other hand, suggest that the influence of the previous stimulus intensity increases with an increase in ITI, which is counter to expectations. The new regression model (a) provides a simple explanation for the counterintuitive results obtained with the earlier model, (b) shows that assimilation in perception or memory can appear as contrast, and (c) reduces to a simpler model for longer ITIs.

Although considerable effort in psychophysics has been devoted to determining the form of the psychophysical function (for references, see Krueger, 1989), there are other aspects of psychophysical data that merit attention. For example, recent research has shown that the sequential structure of magnitude scaling data provides important information about underlying psychological processes (DeCarlo, 1989/1990; DeCarlo & Cross, 1990). The present article extends this research by determining how the intertrial interval (ITI) affects the sequential structure of data from magnitude estimation and cross-modality matching experiments. The focus is on two time series regression models. The models are of interest because they provide an empirical framework for the study of sequential effects and because of their relation to theoretical models of judgmental and perceptual processes in magnitude scaling. The first section of the article reviews the regression models.

Dynamic Regression Models

Stevens (e.g., 1975) showed that subjects' responses in magnitude scaling experiments are a power function of stimulus intensity. The relation can be linearized using logarithms as follows:

$$\log R_t = \beta_0 + \beta_1 \log S_t + e_t, \tag{1}$$

where R_t is the response magnitude on Trial t, S_t is the stimulus intensity on Trial t, and e_t is an error term. Equation 1 differs from the usual expression of Stevens's power law (in log-log form) in that the subscript t makes the time series nature of the data explicit: Most psychophysical data, as well as psychological data in general, are ordered in time. It is important to recognize this temporal ordering in order to obtain information about underlying processes.

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A basic difficulty with Equation 1 is that a large body of research has shown that it is not complete, because the error term e_t shows systematic variation. For example, a typical finding is that the error of the current trial is correlated with errors from previous trials (see DeCarlo & Cross, 1990). The implication is that Equation 1 should be generalized in order to account for the autocorrelation. Two generalizations of Equation 1 have been considered in recent psychophysical research. The first model, introduced by Jesteadt, Luce, and Green (1977), generalizes Equation 1 by including the previous log stimulus and previous log response as regressors, as follows:

$$\log R_{t} = \alpha_{0} + \alpha_{1} \log S_{t} + \alpha_{2} \log S_{t-1} + \alpha_{3} \log R_{t-1} + e_{t}$$
 (2)

(α is used to distinguish the model from Equation 3 below). A number of researchers have fit Equation 2 to magnitude scaling data (e.g., DeCarlo & Cross, 1990; Green, Luce, & Duncan, 1977; Jesteadt et al., 1977; Ward, 1979, 1987). The usual results are that the coefficient of $\log S_{t-1}(\alpha_2)$ is negative and the coefficient of $\log R_{t-1}(\alpha_3)$ is positive. The finding of a negative α_2 has been interpreted as showing that the previous stimulus intensity exerts a contrastive influence on the current perception (e.g., Ward, 1979). The finding of a positive α_3 has been interpreted as showing that an assimilative response heuristic is used (see Equation 15 of DeCarlo & Cross, 1990; Ward, 1979).

The second generalization of Equation 1 that has been proposed is

$$\log R_{t} = \beta_{0} + \beta_{1} \log S_{t} + \beta_{2} \log S_{t-1} + \rho e_{t-1} + u_{t}$$
 (3)

(DeCarlo, 1989, 1989/1990; DeCarlo & Cross, 1990), where $\rho e_{t-1} + u_t$ is a first-order autoregressive, or AR(1), error process, with e_{t-1} representing systematic error and u_t random error (u_t is assumed to have zero mean, constant variance, and no correlation with previous values of itself, e_{t-1} , and the regressors). Equation 3 differs from Equation 2 in that it attributes autocorrelation to an AR(1) error process rather than to log R_{t-1} ; the difference between the two models is shown below.

I thank Mark Waits for conducting Experiment 1, Matthew Baharlias for conducting Experiment 3, and Christopher M. Ring for his assistance in Experiment 2.

The usual results for Equation 3 are that the coefficient β_2 and the autocorrelation parameter ρ are both positive. The finding of a positive β_2 has been interpreted as reflecting an assimilative or additive perceptual or memory effect, in the sense that, for constant $\log S_i$, the current perception increases in magnitude with increases in $\log S_{i-1}$. The autocorrelation parameter ρ has been interpreted as providing a measure of the relativity of judgment to short-term (the previous response and perception) and long-term (a modulus and standard) frames of reference (see Equation 17 of DeCarlo & Cross, 1990). It has also been shown that the judgmental effect, as measured by ρ , can be manipulated experimentally by varying the instructions (DeCarlo, 1989/1990; DeCarlo & Cross, 1990).

It should be evident from the above that a basic difference between Equations 2 and 3 is that the coefficient of $\log S_{r-1}$ is typically negative for fits of Equation 2 but is consistently positive for fits of Equation 3. Thus, the conclusion as to whether the perceptual/memory effect is contrastive or assimilative hinges largely on which model one assumes is correct. This is clearly not a very satisfactory state of affairs. It has recently been shown, however, that Equation 3 offers insight into this difficulty, because it can be rewritten in a form similar to that of Equation 2 (DeCarlo, 1989, 1989/1990; DeCarlo & Cross, 1990). The alternative form of Equation 3, which is derived below, shows that a positive coefficient for $\log S_{r-1}$ in Equation 3 is consistent with a negative coefficient for $\log S_{r-1}$ in Equation 2. In short, Equation 3 unifies what appear to be contradictory findings.

The purpose of the present article is to examine the findings of contrast and assimilation in Equations 2 and 3, respectively, in closer detail by manipulating the intertrial interval. The idea motivating the experiments presented below is that if the coefficient of $\log S_{t-1}$ does in fact reflect the influence of the previous stimulus intensity on the current perception, then this influence should decrease in magnitude when the ITI is increased, irrespective of whether the effect is assimilative or contrastive. Manipulation of the ITI, therefore, allows a simple but important comparison of Equations 2 and 3.

Method

The ITI was varied within subjects in two magnitude estimation experiments (1 and 2; different types of instructions were used in each experiment) and a cross-modality matching experiment (3) where lines were matched to loudness.

Subjects

The subjects were 34 undergraduates enrolled in introductory psychology courses at the State University of New York at Stony Brook; they received course credit for participating in the experiment. Twelve of the subjects participated in Experiment 1 (ratio magnitude estimation), 14 in Experiment 2 (magnitude estimation), and 8 in Experiment 3 (ratio cross-modality matching). All subjects claimed to have normal hearing.

Apparatus

Ratio magnitude estimation and cross-modality matching. A General Radio Company oscillator was used to generate 1000-Hz

tones. Twelve tones, ranging from 40 to 89.5 dB (SPL) in 4.5-dB steps, were presented binaurally through Grason Stadler headphones (TDH-39); each presentation was 1 s in duration. The presentation of the stimuli was controlled by an IBM PC. Each subject was run one at a time in a sound-attenuating chamber (Industrial Acoustics Company) that contained headphones, a terminal, an intercom, and a KAT. The KAT is a pad with a surface that maps to the terminal; movements of a stylus or finger across the surface of the KAT moved an arrow on the terminal.

The order of presentation of the stimuli was determined by sequences of 120 trials generated by the uniform probability generator of SAS (see SAS Institute, Inc., 1985a). The selected sequences (12 total) had at least five presentations of each stimulus intensity. The autocorrelation function and partial autocorrelation function (see Results section) for each sequence were examined; the selected sequences had no significant correlations for at least the first five lags.

Magnitude estimation. A General Radio Company noise generator was used to produce noise bursts of 3 s duration. Seventeen noise bursts, covering a 48-dB range (SPL) in 3-dB steps, were presented according to one of two sequences of 60 trials. (The uniform probability generator of SAS was used to generate a single sequence of 120 trials, which was divided in two.) The noise bursts were taped and were played back to the subjects, who were run in separate groups of 7 each, using a Hewlett-Packard reel-to-reel tape recorder (model number 3968A) and a single 6-in. speaker. The most intense noise burst was measured as approximately 98 dB, using a sound meter held about 5 ft (1.5 m) in front of the speaker. (Note that because the bursts were presented to each group over a speaker, the actual sound pressures experienced by the subjects varied from subject to subject; the relative sound pressures, however, were the same.)

Procedure

Ratio magnitude estimation. Each subject participated in two sessions, one for each ITI (6 s and 20 s), which were separated by 1 to 4 days. The subjects were first given a practice session, in which they were required to make numerical estimates of eight line lengths, approximately 1.5, 3, 6, 12, 24, 48, and 192 mm in length, presented at least once each for a total of 12 trials. The instructions (ratio magnitude estimation, presented below) were the same as those used in the experiment, with the substitution of the word line-length for loudness.

Upon completion of the first practice session, the subjects were given a chance to ask questions and were then given a second practice session, which consisted of 12 practice trials with the 12 stimuli used in the experiment. Subjects were told that the purpose was to familiarize them with the range of stimuli used in the experiment. Upon completion of the second practice session, subjects were given an opportunity to ask questions.

For the experiment, each stimulus was presented either every 6 s or every 20 s. depending on the condition (ITI). Each session consisted of 120 trials. The order of sessions (ITIs) was determined by coin tosses, with the restriction that half of the subjects experienced the 6-s ITI first and the other half experienced the 20-s ITI first. Subjects called out their responses; the experimenter, who was seated in an adjoining chamber, recorded their responses.

The instructions for both ITIs were as follows:

You will be presented with a series of tones that vary in loudness. Your task is to indicate how loud each tone seems by assigning a number to its loudness. Use any number you like for the first tone. Then assign your numbers so that the ratio of the current number to the previous number matches the ratio of the current loudness to the previous loudness. You may use any positive numbers you like, including decimals or fractions. Do not use

zero or negative numbers. If you have any questions, please ask the experimenter now. If not, press the top button to begin.

The instructions are those of ratio magnitude estimation (the "prior reference" instructions of DeCarlo & Cross. 1990).

Magnitude estimation. The 14 subjects were divided into two groups of 7 each. Each group participated in separate sessions in a classroom (i.e., 7 subjects were run at the same time). The subjects were first given six practice trials, in which they judged the loudness of six of the noise bursts. They then received two sessions, one for each ITI (6 s and 16 s), that consisted of 60 trials per session. The sessions were separated by a 5-min rest period. The first group of 7 subjects received the 6-s ITI session first, followed by the 16-s ITI session (the order of ITIs was determined by a coin toss). The order of ITIs was reversed for the second group of 7 subjects; the stimulus sequences were also balanced across the two ITIs. The instructions for both ITIs were as follows:

You will be presented with a series of noise bursts that vary in loudness. Your task is to indicate how loud each noise seems by assigning a number to its loudness. Use only one loudness, any one you like, and its number as a reference point. Try to make all your judgments relative to this reference point. That is, assign your numbers so that the ratio of the current number to the reference number matches the ratio of the current loudness to the reference loudness. You may use any positive numbers you like, including decimals or fractions. If you have any questions, please ask them now.

The instructions are those of free magnitude estimation (the "fixed reference" instructions of DeCarlo & Cross, 1990). Subjects wrote their responses on response sheets, which were numbered from 1 to 60 on the first two sheets (first ITI) and 61 to 120 on the second two sheets (second ITI). The response sheets were collected at the end of the experiment, and the responses were entered into a spreadsheet.

Ratio cross-modality matching. The procedure was identical to that of Experiment 1 above (ratio magnitude estimation), with the following exceptions. For the first practice session, subjects were required to enter line lengths in response to the numbers 2, 3, 5, 7, 10, 15, 20, 30, 50, 75, 125, and 200; the 12 numbers were presented in a random order for a total of 12 trials. For the second practice session (12 trials), subjects assigned line lengths to the 12 stimulus intensities used in the experiment.

The instructions for the experiment were the same as those used for ratio magnitude estimation, with the substitution of the word *line-length* for *number*. A line appeared in the middle of the terminal approximately 0.5 s after the offset of each tone. The initial length of the line was one of 50 values determined by sequences generated by the uniform probability generator of SAS. The 50 lengths covered approximately the full range. The selected initial-length sequences had no significant autocorrelations for at least the first five lags of the autocorrelation function and no significant cross-correlations with the stimulus sequence it was paired with for at least the first five lags. (See the Results section for more information about these functions.)

Subjects used the KAT to adjust the length of each line. Moving a stylus across the surface of the KAT increased or decreased the line length; movements to the right increased the line length, whereas movements to the left decreased the line length. The smallest line that subjects were able to produce was about 2 mm, and the longest was about 203 mm.

For the short (nominal) ITI, each tone was presented approximately 2 s after a line was entered; for the long ITI, each tone was presented about 15 s after a line was entered. Subjects proceeded at a rapid pace (about 3 s per response), except of course for the

constraint introduced by the nominal ITIs. (The actual ITIs, therefore, were approximately 5 s and 18 s.)

Results

Mean and Variability of Responses

Figure 1 presents, separately for each ITI and experiment (ratio magnitude estimation, magnitude estimation, and ratio

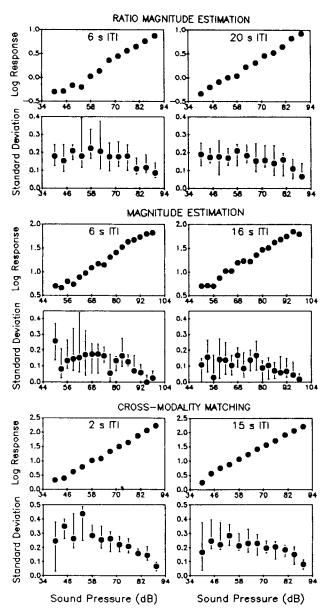


Figure 1. Experiments 1-3: Ratio magnitude estimation of loudness, magnitude estimation of loudness, and ratio cross-modality matching of line length to loudness. (The upper panels for each experiment present, separately for each intertrial interval [ITI], the medians across subjects of the mean log responses to each sound pressure level; for ratio cross-modality matching, responses are line lengths in millimeters. The lower panels present the medians and interquartile ranges across subjects of the standard deviations of the log responses.)

cross-modality matching, respectively) the medians (across subjects) of the mean log responses to each sound pressure level (shown in the upper left and right panels for each experiment). The trends are approximately linear. The lower panels for each experiment show the medians and interquartile ranges (across subjects) of the standard deviations of the log responses. The standard deviations appear to be approximately constant throughout the range, with perhaps a decrease for the most intense sound-pressure levels. This result has frequently been found in magnitude estimation experiments (e.g., see Marley & Cook, 1986).

Time Series Analysis of Residuals

The autocorrelation function (ACF), partial autocorrelation function (PACF), and cross-correlation function (CCF) for the residuals of Equation 1, \hat{e}_i , were computed and plotted for each subject. The (estimated) ACF is the correlation of residuals separated by lags of 1, 2, 3, and so on. The PACF is similar, except that correlations for intermediate lags are partialed out (see Box & Jenkins, 1976). For an AR(1) process, the ACF is an exponentially decaying function of the lag, whereas the PACF cuts off abruptly after the first lag. The CCF is the cross-correlation of Equation 1's residuals with the lagged log stimulus intensities.

Figures 2-4 present, separately for each ITI and experiment, the group ACF, PACF, and CCF plots for the residuals of

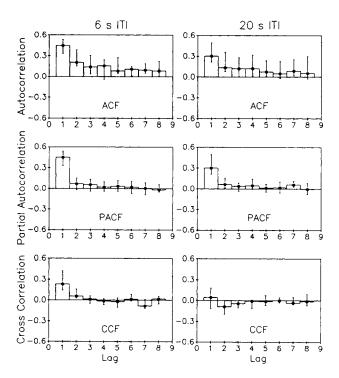


Figure 2. Experiment 1: Ratio magnitude estimation of loudness. (Shown are the group [medians and interquartile ranges across subjects] autocorrelation functions [ACF], partial-autocorrelation functions [PACF], and cross-correlation functions [CCF] for the residuals of Equation 1. The functions are plotted separately for each intertrial interval [ITI].)

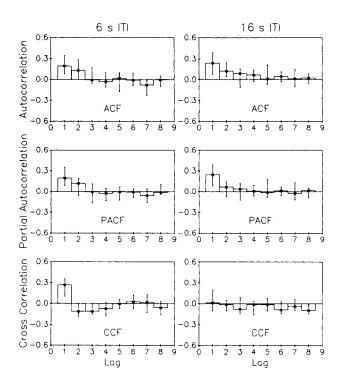


Figure 3. Experiment 2: Magnitude estimation of loudness. (Shown are the group [medians and interquartile ranges across subjects] autocorrelation functions [ACF], partial-autocorrelation functions [PACF], and cross-correlation functions [CCF] for the residuals of Equation 1. The functions are plotted separately for each intertrial interval [ITI].)

Equation 1. The group plots were determined in two steps. First, the ACFs, PACFs, and CCFs were computed and plotted separately for each subject using PROC ARIMA of SAS (see SAS Institute, Inc., 1985b). The medians and interquartile ranges of the correlations were then computed across subjects for each lag and are shown in the figures. The group plots provide a summary of the individual plots.

The ACF and PACF plots are consistent with a first-order autoregressive error process: There is an approximate exponential decay in the ACF and a cutoff after the first lag in the PACF (cf. DeCarlo & Cross, 1990). Of particular interest is that the CCF plots for all three experiments show a positive correlation between \hat{e}_t and $\log S_{t-1}$ (i.e., a correlation at Lag 1) for the short ITIs, whereas this correlation does not appear for the long ITIs. Figures 2–4 show, therefore, that increasing the ITI eliminates or at least reduces the correlation between \hat{e}_t and $\log S_{t-1}$. The implication is that $\log S_{t-1}$ does not exert an influence on responses for the long ITIs.

Autocorrelation Patterns

Figure 5 presents, separately for each ITI and experiment, the first-order (Lag 1) autocorrelations of the residuals of Equation 1 plotted against the (nominal) difference between successive log stimulus intensities (in dB). The correlations were computed by first fitting Equation 1 to each individual's data and then computing, separately for each log stimulus

difference, the correlation between \hat{e}_t and \hat{e}_{t-1} . The log stimulus differences were grouped so that the number of observations in each interval was roughly equal; the abscissae of the plots show the approximate midpoints of the intervals. The figure presents the medians and interquartile ranges (across subjects) of the correlations. (The figures are similar for plots of the means and standard deviations.) The upper panels of the figure show the results for ratio magnitude estimation, the middle panels show the results for magnitude estimation, and the lower panels show the results for ratio cross-modality matching. For all three experiments, an inverted-V pattern is evident.

Regression Analysis

The left sides of Tables 1–3 present for ratio magnitude estimation (RME), magnitude estimation (ME), and ratio cross-modality matching (RCMM), respectively, the results for Equation 3. The estimates of the coefficients were obtained using PROC AUTOREG of SAS (using Yule-Walker estimation; for technical details, see SAS Institute, Inc., 1985b). The results of significance tests on the coefficient of log S_{t-1} (β_2) and e_{t-1} (ρ) are shown for the individual analyses. The Durbin-Watson test (Durbin & Watson, 1950, 1951) was used to test for positive autocorrelation ($\rho > 0$), using the residuals obtained from a regression of log R_t on log S_t and log S_{t-1} . The upper halves of the tables show the results for the short ITIs; the lower halves show the results for the long ITIs.

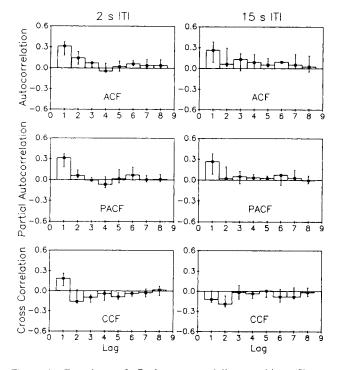


Figure 4. Experiment 3: Ratio cross-modality matching. (Shown are the group [medians and interquartile ranges across subjects] autocorrelation functions [ACF], partial-autocorrelation functions [PACF], and cross-correlation functions [CCF] for the residuals of Equation 1. The functions are plotted separately for each intertrial interval [ITI].)

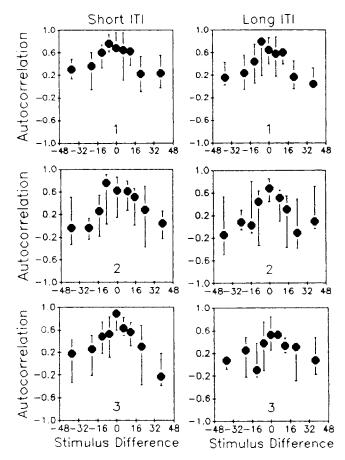


Figure 5. Experiments 1, 2, and 3: Ratio magnitude estimation (top panels), magnitude estimation (middle panels), and ratio cross-modality matching (bottom panels). (Shown are the medians and interquartile ranges across subjects of the first-order autocorrelations plotted separately for each nominal difference between successive log stimulus intensities [in dB]. The left panels show the results for the short intertrial intervals [ITIs], the right panels show the results for the long ITIs.)

The estimates of the coefficient of log S_t (β_1) and e_{t-1} (ρ) are similar in magnitude across the short and long ITIs. Although Experiments 1 and 2 differ in several respects (e.g., 1000 Hz tones vs. noise bursts; 12 vs. 17 intensity levels; 120 trials vs. 60 trials), it is interesting to note that the mean estimates of ρ are larger for both ITIs of the ratio magnitude estimation experiment (1, shown in Table 1) than for the (fixed reference) magnitude estimation experiment (2, shown in Table 2). This result, although between subjects, is consistent with results found by DeCarlo (1989/1990) and DeCarlo and Cross (1990): Ratio magnitude estimation instructions yield larger autocorrelation, because of the increased reliance on the short-term frame of reference.

Of particular importance for the present article is that in all three experiments, the mean estimates of the coefficient of $\log S_{t-1}(\beta_2)$ are smaller for the longer ITIs than for the shorter ITIs (0.066 short vs. 0.016 long for RME, 0.070 short vs. 0.012 long for ME, and 0.073 short vs. -0.020 long for RCMM). For the individual analyses, $\hat{\beta}_2$ is significantly greater than zero (p < .05) for 9 of 12 cases for the 6-s ITI of RME,

Table 1
Experiment 1: Results for Equations 2 and 3

Subject	Equation 3				Equation 2				
	β_1	β_2	ρ	R^2	α_{i}	α_2	α_3	R^2	
~ 4~	-		6-s inte	rtrial inte	erval				
1	.366	.001	.602**	.886	.373	216**	.614**	.844	
2	.391	.031*	.329**	.889	.393	093*	.331**	.877	
2 3	.467	.049*	.743**	.811	.479	287 **	.756**	.830	
4	.603	.075*	.554**	.810	.601	264**	.564**	.779	
5	.499	.058**	.472**	.846	.513	175 **	.504**	.846	
6	.764	.045	.462**	.861	.766	301**	.463**	.850	
7	.494	.114**	.382**	.832	.498	059	.369**	.848	
8	.332	.053**	.420**	.807	.337	081**	.441**	.834	
9	.670	.160**	.471**	.847	.699	132*	.494**	.875	
10	.419	.096**	.163	.871	.423	.011	.224**	.877	
11	.631	.085**	.235**	.896	.632	056	.221**	.895	
12	.292	.020	.348**	.838	.292	081**	.353**	.831	
M	.494	.066	.432	_	.500	145	.444	_	
			20-s int	ertrial int	erval				
1	.548	.037	.443**	.812	.554	200**	.462**	.823	
	.348	021	.012	.885	.348	040	.056	.885	
2 3	.584	.079**	.347**	.844	.580	120*	.329**	.840	
4	.522	012	.480**	.911	.521	284**	.516**	.889	
5	.567	.028	.681**	.875	.572	363**	.702**	.857	
6	.544	.013	.218*	.868	.543	113*	.222*	.869	
6 7	.554	.021	.446**	.870	.542	261**	.465**	.846	
8	.340	.027**	.263**	.920	.342	065*	.284**	.916	
8 9	.544	.039*	.661**	.904	.530	341**	.673**	.885	
10	.481	.031*	.171	.909	.481	046	.160	.907	
11	.564	021	.191*	.895	.563	151**	.225*	.889	
12	.464	030	.242**	.868	.462	168**	.280**	.862	
М	.505	.016	.346	_	.503	-,179	.365	_	

^{*} p < .05. ** p < .01.

for 8 of 14 cases for the 6-s ITI of ME, and for 6 of 8 cases for the (nominal) 2-s ITI of RCMM. In contrast, the estimates are significant for only 4 out of 12 cases for the 20-s ITI of RME, for 3 out of 14 cases for the 16-s ITI of ME, and for 0 of the 8 cases for the 15-s ITI of RCMM.

The right sides of Tables 1–3 present the results for Equation 2. The mean estimates of the coefficients of $\log S_t$ and $\log R_{t-1}$ are close in magnitude to those obtained for $\log S_t$ and e_{t-1} for Equation 3. The results differ from those obtained for Equation 3, however, in that for all three experiments, the mean estimates of the coefficient of $\log S_{t-1}(\alpha_2)$ are larger in absolute magnitude for the longer ITIs than for the shorter ITIs (-0.145 short vs. -0.179 long for RME, -0.047 short vs. -0.120 long for ME, and -0.151 short vs. -0.217 long for RCMM). The significance tests for the individual analyses show similar patterns across the short and long ITIs. (It should be noted that the tests have low power because of multicollinearity.)

Discussion

Of central interest in the present article is the effect of the intertrial interval on the coefficient of $\log S_{t-1}$ in Equations 2 and 3. A typical interpretation of this coefficient is that it reflects the influence of the previous stimulus intensity on the

perception of the current stimulus. If this is the case, then the magnitude of the influence should be smaller when the previous stimulus intensity is farther away in time, that is, when the intertrial interval is increased. The results for Equation 3 are in agreement with this prediction. As the left sides of Tables 1–3 show, the mean estimates of the coefficient of log S_{t-1} for Equation 3 were smaller for the longer ITIs than for the shorter ITIs in all three experiments. Similarly, the cross-correlation functions of Figures 2–4 show that the residuals of Equation 1 tended to be positively correlated with $\log S_{t-1}$ for the short ITIs, but not for the long ITIs. Thus, the results for Equation 3 show that the (assimilative) influence of the previous stimulus intensity decreases with an increase in ITI, which is as expected.

The results for Equation 2, on the other hand, present a very different picture. As the right sides of Tables 1–3 show, the mean estimates of the coefficient of $\log S_{t-1}$ were negative and larger in absolute magnitude for the longer ITIs than for the shorter ITIs in all three experiments. This result poses a problem for the usual interpretation of Equation 2, which is that the negative coefficient of $\log S_{t-1}$ reflects a contrastive influence of the previous stimulus intensity on the current perception. If this was the case, then the influence should have decreased in magnitude when the stimuli were more widely separated in time (longer ITI), and not have increased

Table 2	
Experiment 2: Results ;	for Equations 2 and 3

Subject		Equa	tion 3	Equation 2				
	β_1	β_2	ρ	R^2	α_{i}	α_2	α3	R^2
			6-s inte	ertrial int	erval			
ì	.433	.053*	063	.872	.433	.070	042	.870
$\frac{2}{3}$.490	.061**	.164	.947	.491	011	.147	.948
3	.315	.027	.428**	.880	.312	−.109*	.407**	.868
4	.527	.056*	.433**	.894	.516	181*	.404**	.875
5	.341	009	.202	.931	.341	082	.211	.928
6	.643	.113**	.097	.831	.643	.090	.028	.832
7	.694	.148**	.340**	.916	.700	064	.327**	.924
8	.520	.116**	.279**	.843	.520	001	.221	.819
9	.574	.105**	.411**	.834	.583	101	.370**	.820
10	.598	005	.197	.866	.595	123	.188	.858
11	.763	.085	.133	.859	.766	021	.147	.857
12	.457	.050	.070	.848	.458	.033	.035	.846
13	.761	.176**	.427**	.774	.760	110	.341**	.749
14	.457	.010	.107	.898	.456	044	.106	.895
M	.541	.070	.230	_	.541	047	.207	_
			16-s inte	ertrial int	terval			
1	.459	.016	.269**	.933	.457	116	.273*	.92€
1 2 3	.460	016	054	.911	.460	.008	052	.912
3	.315	015	022	.868	.315	010	016	.869
4	.461	.005	.290**	.924	.462	131*	.304*	.912
5 6	.358	006	.075	.921	.358	038	.089	.919
6	.589	067*	.061	.913	.588	098	.051	.910
7	.736	037	.226*	.924	.728	−.245 *	.272	.919
8	.505	.062*	.514**	.873	.499	188 **	.478**	.850
9	.388	.061	.398**	.752	.389	088	.397**	.772
10	.561	014	.203	.906	.560	139	.216	.902
11	.645	.067	.498**	.854	.645	256**	.527**	.848
12	.451	.020	.225**	.870	.454	102	.273*	.864
13	.706	.033	.298**	.725	.695	164	.249*	.707
14	.455	.057**	.401**	.915	.458	115*	.398**	.912
M	.506	.012	.242	_	.506	120	.247	

^{*} p < .05. ** p < .01.

as found above. At the very least, the results demand that the usual interpretation of Equation 2 be revised.

As was noted in the introduction to this article, it has previously been shown that Equation 3 unifies results that appear to be contradictory (i.e., the attainment of assimilation or contrast, depending on which model is fit; see DeCarlo, 1989, 1989/1990; DeCarlo & Cross, 1990). This unification is possible because Equation 3 implies a parameter constraint in Equation 2. I now show that Equation 3 also offers insight into the counterintuitive results obtained for Equation 2, that is, the increase in contrast for longer ITIs. Once again, an understanding of the parameter constraint that Equation 3 implies for Equation 2 is crucial. The relation between the two models can be shown by first rewriting Equation 3 as follows:

log
$$R_t = \beta_0 + \beta_1 \log S_t + \beta_2 \log S_{t-1} + e_t$$
,
 $e_t = \rho e_{t-1} + u_t$,

where the error component has been separated from the systematic part of the model. It follows from the above that $e_t = \log R_t - \beta_0 - \beta_1 \log S_t - \beta_2 \log S_{t-1}$, which in turn implies

that

$$e_{t-1} = \log R_{t-1} - \beta_0 - \beta_1 \log S_{t-1} - \beta_2 \log S_{t-2},$$
so
$$e_t = \rho e_{t-1} + u_t$$

$$= \rho \log R_{t-1} - \rho \beta_0 - \rho \beta_1 \log S_{t-1} - \rho \beta_2 \log S_{t-2} + u_t,$$

and substituting for e_i in the first equation gives

$$\log R_{t} = \beta_{1} \log S_{t} + (\beta_{2} - \rho \beta_{1}) \log S_{t-1} + \rho \log R_{t-1} - \rho \beta_{2} \log S_{t-2} + u_{t},$$
 (4)

where the intercept, $(1 - \rho)\beta_0$, has been dropped (it is irrelevant to the argument). Equation 4 is simply an alternative expression of Equation 3; it is important because it shows what happens when Equation 2 is fit to the data, when Equation 3 is in fact the correct model. This can be seen by noting that when $\log S_{t-2}$ is omitted, the regressors remaining in Equation 4 are the same as those in Equation 2. It should be noted that omission of $\log S_{t-2}$ does not bias the estimates of the coefficient of $\log S_t$ or $\log S_{t-1}$, because $\log S_{t-2}$ is by design uncorrelated with these regressors. Thus, Equation 4 shows that if Equation 3 is the correct model, then the

Table 3
Experiment 3: Results for Equations 2 and 3

Subject	Equation 3				Equation 2			
	β_1	β_2	ρ	R^2	α_1	α_2	α_3	R^2
			2-s inte	ertrial inte	erval			
1	.746	014	.338**	.787	.736	304**	.355**	.774
2	.761	.084**	.361**	.874	.751	184*	.325**	.862
3	.755	.079*	.176	.794	.757	051	.175	.792
4	.785	.108**	.237*	.850	.782	059	.215*	.854
5	.675	.044	.387**	.690	.667	254**	.401**	.692
	.792	.086*	.424**	.836	.777	244 **	.392**	.809
6 7	.707	.098**	.317**	.803	.706	120	.317**	.814
8	.919	.096**	.141	.873	.918	.012	.081	.873
M	.767	.073	.298	_	.762	151	.283	_
			15-s int	ertrial int	erval			
1	.889	033	.242**	.868	.887	309**	.288**	.859
2	.883	055	.023	.888	.882	112	.062	.887
2 3	.656	040	.408**	.901	.653	339**	.434**	.883
4	.727	.002	.027	.898	.726	028	.042	.898
5	.584	.002	.165	.777	.584	100	.168	.772
6	.813	021	.259**	.867	.811	280**	.298**	.856
6 7	.681	.013	.419**	.873	.674	300**	.447**	.870
8	.840	028	.225*	.808	.829	270**	.254**	.795
М	.759	020	.221		.756	217	.249	

^{*} p < .05. ** p < .01.

coefficient of log S_{t-1} in Equation 2 (α_2) is actually an unbiased estimate of $\beta_2 - \rho \beta_1$. It follows that $\alpha_2 = \beta_2 - \rho \beta_1$ will be negative if $\beta_2 < \rho \beta_1$, which appears to be the typical case (see Tables 1–3). The parameter constraint explains why the coefficient of log S_{t-1} is positive for fits of Equation 3 (i.e., β_2 is small and positive) and negative for fits of Equation 2 (i.e., $\alpha_2 = \beta_2 - \rho \beta_1$ is negative, because $\beta_2 < \rho \beta_1$). For additional examples and discussion, see DeCarlo and Cross (1990).

The important aspect of Equation 4 for the present article is that it suggests why the (negative) coefficient of $\log S_{t-1}$ for Equation 2 increases in absolute magnitude with an increase in ITI: The coefficient is larger because β_2 is smaller. That is, it follows from the parameter constraint of Equation 4 that a decrease in (positive) β_2 (as shown in Tables 1-3) will yield an increase in (negative) $\alpha_2 = \beta_2 - \rho \beta_1$. For example, the mean estimates of β_1 , β_2 , and ρ for fits of Equation 3 to the short ITI data of Experiment 1a above are (from Table 1) 0.494, 0.066, and 0.432, respectively. Equation 4 shows that the coefficient of log S_{t-1} predicted for a fit of Equation 2 is $0.066 - 0.432 \times 0.494 = -0.147$, which is close to the mean estimate actually obtained ($\alpha_2 = -0.145$, from the right side of Table 1). As can be seen in Table 1, the mean $\hat{\beta}_2$ decreased for the longer ITI (from 0.066 to 0.016), and it follows from Equation 4 that the coefficient of $\log S_{i-1}$ for Equation 2 (α_2 = $\beta_2 - \rho \beta_1$) will be larger in absolute magnitude; the right side of Table 1 shows that this was in fact the case. (The mean estimate increased from -0.145 to -0.179; note that ρ was also smaller for the longer ITI, but not enough to offset the effect of the decrease in β_2 .) Thus, Equations 3 and 4 provide a simple explanation for the apparent increase in contrast: The increase occurs because of the decrease in assimilation.

The relation between Equations 2 and 3, as shown by Equation 4, clarifies results that would otherwise be puzzling.

In sum, the coefficient of $\log S_{t-1}$ in Equation 3 was positive and decreased in magnitude with increased ITI in all three experiments. The perceptual or memory interpretation of this result is that the previous stimulus intensity exerts less of an influence on the current perception when the ITI is increased, perhaps because the previous perception decays in memory during the ITI. It should also be noted that Equation 3 simplifies for longer ITIs, because, as shown by Tables 1–3, the estimates of the coefficient of $\log S_{t-1}$ were close to zero in all three experiments, whereas this was not the case for Equation 2. Equation 3, therefore, offers a more parsimonious model for longer ITIs. The present results, together with previous research, show that Equation 3 offers a simple, unifying model of sequential effects in magnitude scaling.

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