Supplemental Materials for:

Reasons for Cooperating in Repeated Interactions: Social Value Orientations, Fuzzy Traces, Reciprocity, and Activity Bias

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Details of Time Series Analysis

Variables measured repeatedly on successive occasions generate data that are called *time series*. In general, such data are not stochastically independent, have correlated residuals or error terms, and are characterized by variance that does not remain constant over the time series. For these reasons, time series cannot be analyzed with conventional statistical procedures that assume independent and identically distributed data sets. The appropriate analytical techniques are provided by *time series analysis* (Bisgaard & Kulahci, 2011; Chatfield, 2003; Shumway & Stoffer, 2006; Yaffee & McGee, 2000; Yanovitzky & VanLear, 2008).

The SPSS Expert Modeler (Norušis, 2005, 2011) automatically identifies and estimates parameters for the best-fitting ARIMA (autoregressive integrated moving average) or exponential smoothing model—whichever provides the better fit—for any time series. It also provides suitable measures of fit, thus eliminating the need to identify appropriate models through trial and error, and it also generates results of appropriate significance tests. ARIMA (p, d, q) models incorporate three parameters. The parameter p specifies the number of orders of autoregression in the model, indicating which previous values from the time series determine current values—for example, an autoregression of order of 2 specifies that the value of two previous values determine the current value. The parameter d specifies the order of differencing applied to the series before estimating models, differencing being necessary when trends are present, because ARIMA modeling assumes stationarity, and differencing detrends nonstationary time series. Thus first-order differencing with $d = 1$ accounts for linear trends, second-order differencing with $d = 2$ accounts for quadratic trends, and so on. The final parameter q specifies the number of moving average orders in the model, showing the extent to which deviations of previous values from the series mean (random shocks) determine current values. For example, $q = 2$ specifies that deviations from the mean over each of the last two values determine current values of the series.

Exponential smoothing models are used to fit time series in which current values are determined by past values, not necessarily weighted equally, but assigned exponentially decreasing weights according to their distance from the current value. The key smoothing parameter α ranges from 0, when all previous values are equally weighted in determining the current value, to 1 when the current value is determined solely by the immediately preceding value. A simple exponential smoothing model fits time series without trend or seasonality; it is roughly equivalent to an ARIMA (0, 1, 1) model with one order of differencing and one order of moving average. When there is systematic trend in the data, a simple model will not provide an adequate fit, and double or multiple exponential smoothing is required. A Holt linear trend model is a model with two smoothing parameters, μ (level or intercept) and β (trend), and a Brown linear trend model is a simpler, one-parameter special case of a Holt model, when the parameters are equal.

These techniques work best with longer time series than those generated in our experiment, but our relatively short time series, though inadequate for precise estimation of parameter values and forecasting, are tolerable for identification of basic models and rough-and-ready assessments of model fit (Bence, 1995; Cooper & Madden, 2010; Wang, Wu, Li, & Chan, 2008).

Experiment 1

Figure 6 (reproduced below) shows the sequence plots of mean exit nodes over the 20 rounds of Experiment 1, under fixed pairing and random pairing, in each of the four experimental games. It is obvious by inspection of Figure 6 that there was more cooperation under fixed than random pairing across almost all 20 rounds in all games except the decreasing payoff-difference game. We performed time series analysis by fitting either an exponential smoothing model or an autoregressive integrated moving average (ARIMA) model, depending on which of the two provided the better statistical fit, to the mean exit nodes, recorded for each round, in each of our treatment conditions—four distinct games crossed with fixed or random pairing. Exponential smoothing models generally include a parameter indicating the influence on scores of the sequence of preceding scores in the series (unequally weighted) and a second parameter indicating the degree of linear or nonlinear trend in the data. When an exponential smoothing model provided the best fit, we estimated the value of the model fit statistic stationary R^2, the preferred estimate of the proportion of the total variance in the time series explained by the model, and the Ljung-Box statistic Q with its associated p value, an indication of confidence that the model is correctly specified. For the Ljung-Box Q statistic, a p value of less than .05 suggests the presence of significant structure in the time series *not* explained by the model. When an ARIMA model provided the best fit, we recoded only the number and type of parameters used to identify the model and did not attempt to estimate the parameters. In an ARIMA(p, d, q) model, the value of p represents the number of autoregression parameters, indicative of the dependence of scores on preceding scores; *d* the degree of differencing, indicative of linear or nonlinear trend; and *q* the number of moving average parameters, indicative of the dependence of scores on preceding random shocks. We relied on the SPSS Expert Modeler to select the best-fitting models to the time series.

In the constant payoff-difference game under fixed pairing, the best-fitting model is an ARIMA(0, 0, 0) model, indicating a lack of temporal structure in the data; but under random pairing the best fit is provided by a Holt model, an exponential smoothing model that fits time series with autocorrelation and linear trend. For the Holt model, stationary $R^2 = .68$ and Ljung-Box $Q = 17.45$, $p = .36$, indicating a reasonably good model fit and confidence that the model is correctly specified. This confirms that the decline in cooperation over rounds under fixed pairing that is apparent in the sequence plot (Figure 6) is essentially linear and statistically significant.

In the constant-sum game, once again, the best-fitting model under fixed pairing is an ARIMA(0, 0, 0) model, indicating a lack of temporal structure in the data, and under random pairing the best fit is a Holt model, with stationary $R^2 = .80$ and Ljung-Box $Q = 13.21$, $p = .66$. We can be confident that the decline in cooperation over rounds under random pairing is linear and statistically significant.

In the increasing payoff-difference game under fixed pairing, a Holt model provides the best fit, with stationary $R^2 = .77$ and Ljung-Box $Q = 23.76$, $p = .09$, indicating a significant linear decline in cooperation over rounds, although with *p* so close to .05, we can have only a barely significant degree of confidence that the model is correctly specified. Under random pairing, a Holt model is once again the best fit, this time with stationary $R^2 = .78$ and Ljung-Box $Q =$

23.12, $p = .11$, allowing the same conclusion as for the fixed pairing condition that the decline in cooperation is probably significant and linear.

In the decreasing payoff-difference game, under fixed pairing, a Holt model provides the best fit, with stationary $R^2 = .81$ and Ljung-Box $Q = 12.17$, $p = .73$. Under random pairing, the best fit is a Brown model—a simple one-parameter version of the Holt model, also indicative of linear trend—with stationary $R^2 = .78$ and Ljung-Box $Q = 18.60$, $p = .35$. These results suggest that, under both fixed and random pairing, cooperation declined significantly and linearly over rounds in the decreasing payoff-difference game.

Experiment 2

We performed time series analysis once again on the mean exit nodes per round. Sequence plots of mean exit nodes in the normal-form and extensive-form treatment conditions are shown in Figure 8, from which it is immediately obvious that cooperation was similar in both conditions on almost every round of the game, from the first to the last. In the extensive form treatment condition, a Holt model also provides the best fit, with stationary $R^2 = .81$ and Ljung-Box $Q = 12.17$, $p = .73$. In the normal form, a Holt model once again provides the best fit, with stationary $R^2 = .76$ and Ljung-Box $Q = 15.33$, $p = .50$. We can infer with confidence that a linear decline in cooperation over rounds occurred in both the extensive and normal forms of this game.

Supplemental References

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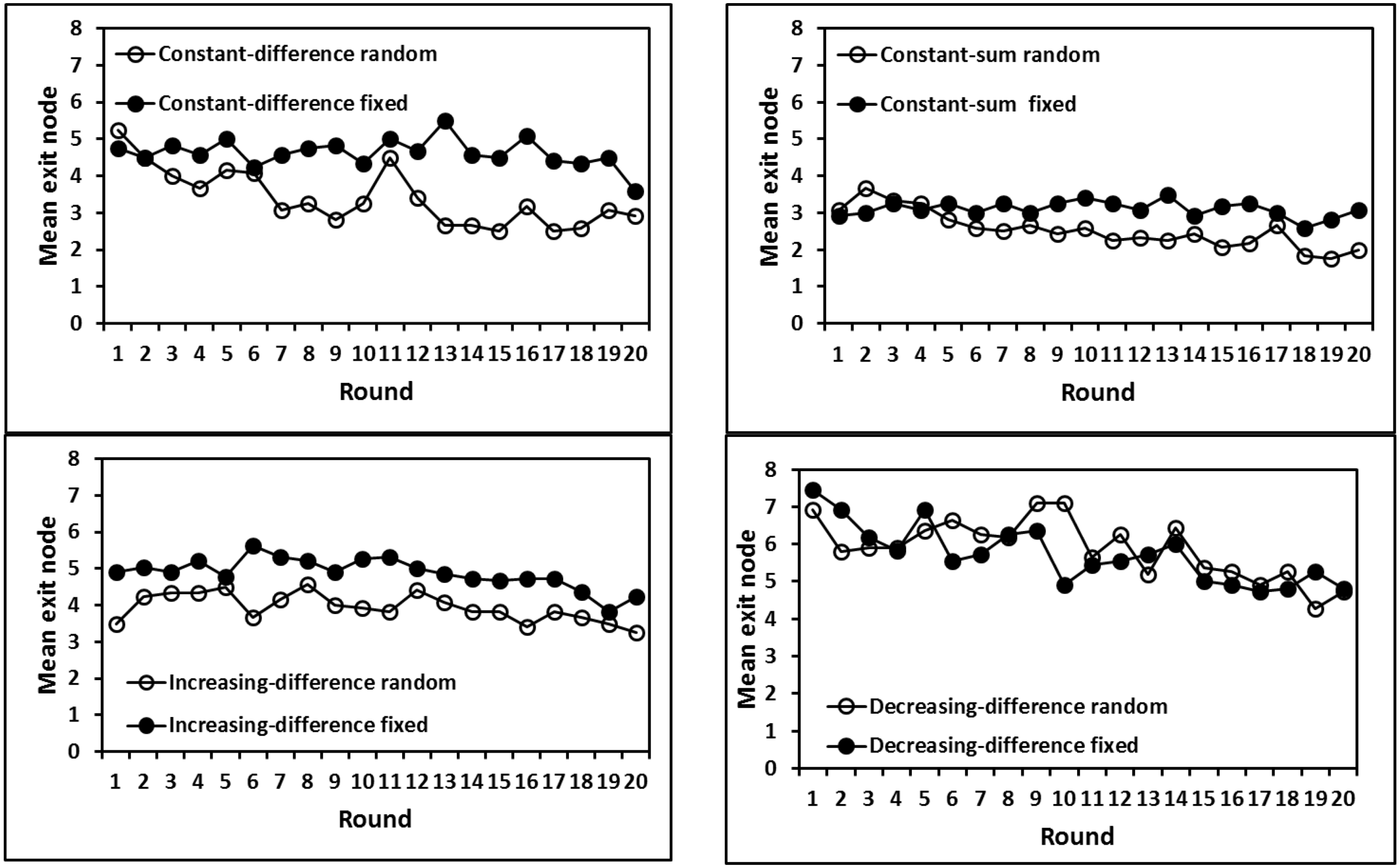

Figure 6. Experiment 1: Sequence plots of mean exit nodes under fixed pairing and random pairing in the four linear Centipede games: constant payoff-difference, constant-sum, increasing payoff-difference, and decreasing payoff-difference.

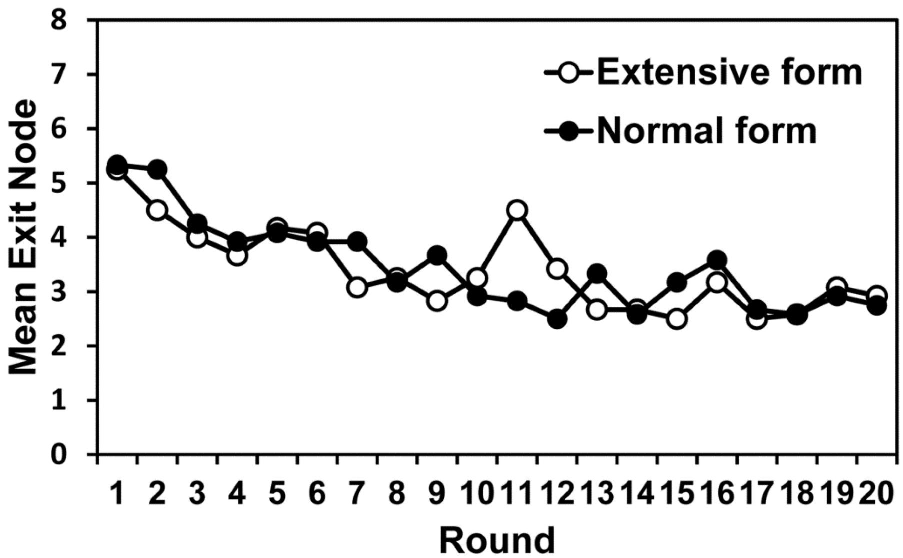

Figure 8. Experiment 2: Sequence plots of mean exit nodes for a constant payoff-difference game played in normal form and extensive form.