Accounting for Statistical Dependency in Longitudinal Data on Dyads

Niall Bolger

Patrick E. Shrout

New York University

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Author Notes:

Niall Bolger, Department of Psychology, New York University, 6 Washington Place, Room 752, New York, NY 10003. Phone 212-998-3890, Fax 212-995-4966, E-mail: niall.bolger@nyu.edu.

Patrick E. Shrout, Department of Psychology, New York University, 6 Washington Place, Room 308, New York, NY 10003. Phone 212-998-7895, Fax 212-995-4966, E-mail: pat.shrout@nyu.edu.

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Abstract

Longitudinal data on dyads have statistical dependencies due to stable and time-varying characteristics of the dyad members and of their environment. This article discusses two ways of estimating these dependencies, one involving multilevel models and the other involving structural equation models. To illustrate each approach, we analyze data on daily reports of anger by males and females in couples where one partner was a law school graduate preparing to take the bar examination.

Accounting for Statistical Dependency in Longitudinal Data on Dyads

Although social and developmental psychology define dyadic processes as an important part of their subject matter, there is still considerable uncertainty in these fields about how to analyze dyadic data. The reason for this uncertainty is that conventional statistical methods are designed for studying independently sampled persons, whereas the most interesting feature of dyadic data is their lack of independence. Moreover, in recent years this problem has been compounded as researchers have increasingly adopted intensive repeated-measures designs to study dyads in natural settings (Bolger, Davis & Rafaeli, 2003). When one collects repeated-measures data on dyads, one must not only contend with nonindependence of the members within the dyad but also nonindependence of the observations within a dyad member.

The goal of this chapter is to present a potential solution to this problem. We present a model for the covariance structure of dyadic diary data, a model that can account for where the dependencies in the data lie, and one that can be used as a baseline for explanatory work on the causal processes that produce the dependencies. As we show, the general model can be estimated using either of two equivalent statistical approaches, a structural equation model (SEM) approach, and a multilevel model approach.

Our general model is related to Kenny and Zautra's Trait-State-Error model (also known as the STARTS model; Kenny & Zautra, 1995, 2001), which used an SEM approach to decompose a person's measured level on some psychological characteristic at a particular time into a component reflecting their typical level, a component reflecting their true current state, and a component reflecting measurement error. Like Kenny &

Zautra, we distinguish stable and time-varying sources of dependence, but we do so in the context of dyads and we do not make adjustments for measurement error.

More directly related to our approach is the Actor-Partner Interdependence Model, also developed by Kenny and his colleagues (e.g., Cook & Snyder, 2005; Kashy & Kenny, 2000; Kenny, 1996). In its application to longitudinal data on dyads, the model assesses the extent to which dyad members influence themselves and their partners over time. Actor effects reflect the extent to which a member's prior score on some variable affects his or her subsequent score on that variable. Partner effects are the extent to which a member's prior score on some variable affects his or her partner's subsequent score. It is important to note that actor effects are estimated controlling for partner effects and vice versa.

Our approach is less ambitious than the Actor-Partner Interdependence Model in the sense that we do not attempt to estimate actor and partner effects. Instead we estimate the covariances between dyad members' scores, covariances that can be the result of causal effects of members on one another or of common environmental events. Furthermore, we distinguish between covariance that is constant over time and covariance that is not (akin to Kenny and Zautra's State-Trait-Error Model). We see the causal modeling of interpersonal and environmental influences as a subsequent analytic step that can be accomplished by adding additional predictors and directed paths to our model.

A third related approach is the model presented by Gonzalez and Griffin (Gonzalez & Griffin, 1997, 1999, 2002; Griffin & Gonzalez, 1995) in which they analyze associations between variables into their components at multiple levels of analysis.

However, whereas Gonzalez and Griffin explicitly estimate dyad-level and individual-level associations, we give priority to the individual level, but we do so in a way that takes account of time-invariant and time-varying dependencies that in their approach would emerge at the dyad level.

Finally, our approach is related to Raudenbush, Barnett and Brennan's work on analyzing dyadic longitudinal data (Barnett, Marshall, Raudenbush, & Brennan, 1993; Raudenbush, Brennan, & Barnett, 1995) in the sense that we present a multilevel model modified to take account of dependencies that are specific to dyadic data. We will elaborate further on these links when we have described our approach in more detail.

The Dyadic Process Model

We first describe some basic features of a dyadic process using as an example reports of anger by each dyad member over time. Figure 1 illustrates the structure of these data. We expect that some persons will report more anger than others, and that anger on one day will tend to be followed by anger on another. Anger will have consequences in the dyad such that anger felt by one partner will often be met by anger in the other. These considerations lead us to ask the following questions: 1) To what extent does the average tendency to be angry covary between partners in an intimate relationship? 2) How strong is the association of anger on one day with anger on the next day within a given person? 3) To what extent is anger in one partner related to anger in the other partner on the same day?

Method

Participants and design. The sample and design was described in detail by Bolger, Zuckerman and Kessler (2000) and will only be briefly described here. In the spring before they graduated, we recruited third year law students who were in romantic relationships with partners of the opposite sex for at least the previous 6 months, and who expected to be living with their partners in the weeks before the state bar examination. We excluded couples if both partners were preparing for the bar exam. Couples were paid $50 for completing the study. Ninety nine couples initially agreed to participate after recruitment material was left at law schools, and a final sample of 68 couples (69%) completed the majority of the study forms. For the current analyses we limited the sample to the 64 couples that had complete data on all relevant variables. Among these couples, the examinee was male in 65% of the dyads. Examinee mean age was 28.9 years (SD = 5.0), and partner mean age was 29.0 (SD = 6.1). Seventy one percent of the couples were married, and couples had been living together for an average of 3.1 years (SD = 3.1). The quality of their relationships was generally high. The mean value of the global Dyadic Adjustment Scale (Spanier, 1976) was 103.2 and the standard deviation was 14.4. Over 90% of the couples were white. All the examinees were law school graduates, and 85% of their mates were college graduates.

At the end of each day each partner rated 18 moods adapted from the Profile of Mood States (POMS; McNair and Lorr, 1992). We focus only on a four-item Anger scale composed of the average of items "annoyed", "peeved", "angry" and "resentful". This scale has been shown to be reliable measure of within-person change over time, with a generalizability coefficient of 0.75 (Cranford et al, 2005). To make our model easy to represent graphically, we focus on a seven day period, days 4 to 10. Because we wished to focus on a period of relative stationarity, we omitted the first three diary days and chose a period that began one month in advance of the examination. Although this cannot be considered a low-stress period, it involved considerably less stress than weeks closer to the event.

Statistical methods

As noted above, we used two approaches to the data analysis, one involving multilevel models and the other involving structural equation models. In the first approach, the relationships among data points displayed in Figure 1 was initially ignored in the organization of the data: Daily reports of anger were treated as the outcome and reports of examinees were not differentiated from those of partners, nor were earlier reports differentiated from later reports. We then applied the following model to the data, one that began to differentiate the source and timing of the reports. In the model, A_{icd} is the anger rating of person *i* (*i*=1 or 2) in couple *c* (*c*= 1 to 64) on day *d* (*d*= 1 to 7).

$$A_{icd} = (I_{1cd})M_{1c} + (I_{2cd})M_{2c} + r_{icd} \qquad \text{Equation 1a}$$

$$M_{1c} = \phi_1 + U_{1c} \qquad \text{Equation 1b}$$

$$M_{2c} = \phi_2 + U_{2c} \qquad \text{Equation 1c}$$

In equation 1a, I_{1cd} is dummy coded to be 1 for the examinee and 0 for the partner, regardless of the couple or day. Similarly, I_{2cd} is dummy coded to be 1 for the partner and 0 for the examinee for all couples and days. These indicator variables allow M_{1c} to be interpreted as the intercept (mean over days) for the examinee in couple *c* and M_{2c} to be the intercept (mean over days) for the partner in the same couple *c*. The term r_{icd} is that part of the Anger rating of person *i* in couple *c* on day *d* that is not explained by the average rating of person *i* in couple *c*. We will say more about this term later.

In equation 1b the intercepts for individual examinees are decomposed into a grand mean for all examinees (ϕ_1) plus a specific mean for the examinee in each couple *c*

(U_{1c}). In multilevel model terminology, the latter is a random effect in a level 2 model. Similarly, equation 1c decomposes the intercepts for partners into a grand mean for all partners (ϕ_2) and a specific mean for partners in each couple *c* (U_{2c}). It is possible to specify that the random effects for an examinee and partner within the same couple are correlated. This is made explicit by specifying that the expected variance covariance matrix of (U_{1c}, U_{2c}) is a 2 by 2 symmetric matrix (G) with the following unique elements, $Var(U_{1c}) = G_{11}$, $Var(U_{2c}) = G_{22}$ and $Cov(U_{1c}, U_{2c}) = G_{12}$. An estimate of the latter value will characterize the degree to which (across couples) examinees whose mean anger ratings are high tend to be paired with partners whose mean anger ratings are also high.

Returning to the residual term, r_{icd}, we note that anger variations within a person can be correlated from day to day, and that the variation of the examinee can be related to that of the partner. If we were to assume a completely general pattern of such covariation this would result in large number of covariance parameters to estimate. In fact, with two persons per couple and seven days, there would be 105 distinct elements to estimate in the resulting 14 by 14 symmetric matrix. We will greatly simplify the estimation of these covariances by assuming that the examine and partner variances are stable over time, that adjacent days are correlated by a lag-1 autoregressive process, and that the examinee-partner covariance is stable over time. These assumptions allow us to fit all 105 covariance elements with only four parameters: the variance of the examinee residuals, the variance of the partner residuals, the covariance of the examinee and partner residuals, and the autocorrelation of lag one residuals over examinee days and partner days.[1]

Unlike the multilevel approach, the SEM approach considers data that are organized by independent unit, in this case dyad. Figure 2 shows a graphical representation of this SEM. Each line of input data contains 14 values, seven for the examinee and seven for the partner. If one or more of these values are missing, special efforts are needed either to impute the values directly, or to estimate the sample covariance matrix using the EM algorithm. To simplify our discussion, we ignore these issues by working with complete data only, although this strategy can only be justified if the data are missing completely at random (see Schafer & Graham, 2002, for more details on estimation in the presence of missing data).

Returning to Figure 2, there are two latent variables represented by ovals, one denoting individual differences (at the couple level) in mean anger for examinees and one denoting similar differences in mean anger for partners. Following Willet and Sayer (1993), these are defined by constraining the loadings of the latent variables to the daily anger reports to be equal to one. These couple-level random variables are assumed to be correlated, as indicated by the double headed arrow connecting the two. In addition to latent means, each anger report is determined by a daily fluctuation represented by the residual (*r*) effect in circles. The daily fluctuation for the examinee is assumed to be correlated with the daily fluctuation of the partner and the size of the fluctuation on one day is assumed to partly determine the size on the following day. On each day the fluctuations are also affected by a random variable (*e*) that is assumed to be uncorrelated with other variables in the system. These assumptions are virtually the same ones we made when considering the data from a multilevel perspective[2].

We fit the data from the multilevel approach using the MIXED procedure of SAS because of the flexibility it affords in modeling the correlation structure of the residuals. To estimate the structural equation model we used EQS version 6.1 (Multivariate Software, 2004). The syntax used in each case is presented in the Appendix.

Descriptive Results

Table 1 shows the means and standard deviations for the seven days in our analysis. The ratings were on a 0 to 4 scale, and it is clear that most of the sample did not experience high levels of anger. Examinees had slightly lower levels of reported anger during this week than their partners, but this difference was not statistically significant.[3] Days 4 and 5 were weekend days, and the tendency for both partners to have slightly less anger on Sunday is apparent in the means. In fact, the mean level of anger for examinees correlates 0.78 with that of partners over the seven days.

Table 1 shows the between person correlations for each of the 14 days, 7 daily reports by the examinee and 7 daily reports by the partner. In the upper left hand quadrant of the matrix are the correlations among anger reports by the examinee. The largest correlations are for adjacent days, and the correlations tend to decline with increasing lag. The correlations for the largest lags are no longer significant, but all the correlations are positive. A similar pattern is observed in the lower right hand quadrant, which contains correlations among the daily reports by the partner. All the correlations are positive, but the largest are for lag 2 and lag 1 comparisons.

The lower left hand quadrant shows the correlations among the examinee and partner reports for the seven days. Many of these correlations fluctuate around zero, some negative and some small and positive. However, the same day correlations tend to be larger, with the median correlation being 0.32. The only other moderate size correlations tend to be for lag 1 associations.

Modeling the Association Patterns

Table 2 shows the results of fitting the model in Figure 2 using multilevel and SEM approaches. The model provides a rough description of the patterns of association, even though the fit indices suggest that the nuances of the relations shown in Table 1 are not well represented (From EQS, NNFI=.73; RMSEA=.10). The two approaches provide very similar estimates and standard errors. For simplicity, we use the estimates from the multilevel approach to make substantive comments.

The grand means for the examinees ($\phi_1 = 0.537$) and their partners ($\phi_2 = 0.617$) show that the majority of the participants report low levels of anger on average. The spread of the distribution of these random effects is indicated by the variance of the level 2 random effects. These are similar for examinees ($G_{11} = 0.08$) and partners ($G_{22} = 0.12$). Because these are not significantly different from each other, a reasonable estimate of the standard deviation of the random effects is the square root of the midpoint 0.10, which is 0.32.

The covariance of the random effects is $G_{12} = 0.045$, yielding a correlation estimate of 0.47. Although the point estimate is suggestive of a medium to large effect, this estimate is not significantly different from zero. The failure to be statistically significant is due to the imprecision of the estimate of this correlation, which is adjusted for measurement error, in the same way that correlations can be corrected for attenuation using classical test theory (Lord & Novick, 1968). When we calculated the sample averages for each respondent over the seven days and correlated these directly, we obtained a correlation of 0.40, which was statistically significant with $p<.001$. As one would expect, this latter estimate is somewhat smaller than the correlation between the latent means because of measurement error.[4]

In addition to the association of the examinee and partner in their tendency to have high or low scores overall, Table 2 shows that there is an association among residual scores of examinees and partners on a given day (multilevel estimate = .134; SEM estimate = .136). This association could be due to events that the members of the dyad shared, such as arguments that lead to unusually high anger ratings, or shared pleasant events that lead to unusually low anger. In this case the covariance reflecting this association is statistically significant, although the implied correlation is modest ($r = 0.26$).

The final association reported in Table 2 is the autocorrelation of residuals on one day with residuals on the next for a given participant. This correlation is estimated to be 0.316 using the multilevel approach, and the small standard error implies that it is reliably different from zero. Part of this correlation could be due to a tendency for persons to be increasing or decreasing steadily in anger (Rogosa, Brandt, & Zimowski, 1982; Rogosa, 1988). We estimated a model that included linear growth effects for examinee and partner and found that neither random effect had reliable variance. When we included a fixed growth parameter only the autocorrelation was reduced from 0.32 to 0.30.

The parameters of the dyadic process model can be used to generate predicted correlations among the 14 daily anger measures, analogous to the actually correlations presented in Table 1. In Table 3 we summarize these predicted correlations. In general, these are reasonably similar to the actual correlations, but it can also be seen that these predicted correlations miss considerable variability within any given time lag.

It is worth considering how much of a given examinee-partner correlation is attributable to influences at the between-person and within-person level. Although the correlation between the mean anger of examinees and partners is substantially greater than the day-level correlation (.469 vs. .262), because most of the variance in anger resides at the daily level (e.g., .08 vs. .42 for examinees and .12 vs. .63 for partners), 75% of the predicted same-day correlation of .292 is due to shared variance at the daily level, whereas only 25% is due to shared variance at the person-level.

Discussion

We have described a model of dyadic longitudinal data that we believe is a useful starting point for researchers whose principal focus is to understand within- rather than between-dyad processes. In this respect our model shares more in common with the Kenny and colleagues models (Kenny & Zautra, 1995, 2001; Kashy & Kenny, 2000; Cook & Snyder, 2005; Kenny, 1996) and the Raudenbush et al. (1995) model than it does with the Gonzalez and Griffin model (Gonzalez & Griffin, 1997, 1999, 2002; Griffin & Gonzalez, 1995). In the Gonzalez and Griffin model, the covariance among measures obtained on multiple individuals in multiple dyads is partialed into within- and between-dyad components. Our model does not estimate dyad-level relationships directly; their influence can only be seen though the correlations between latent variables at the individual level (e.g., between the latent means for anger for examinees and partners.)

As discussed in the methods section, the multilevel model formulation of our model is similar to (and draws on) the work of Raudenbush and colleagues on dyadic data analysis. Their approach was more complex than ours in the sense that they formed replicate-measures subscales of their dependent variable to take account of measurement error. Our model is more complex than theirs, however, in the sense that our error structure handles autocorrelation over time within a person and between persons within a dyad.

Of the three alternative approaches, ours is most similar to a combination of the State-Trait-Error Model and the Actor-Partner-Interdependence Model. Like the State-Trait-Error Model, we show that the relation among variables over time can be decomposed into a stable component, the correlation among latent means, and a time-varying component, consisting of a model of temporal relationships within and between dyad members. Like the Actor-Partner Interdependence Model, we focus on dyadic relationship over time, but, as noted earlier, we limit ourselves to estimating dyadic covariances rather than directed effects that can be interpreted as within-dyad causal influences. We also note that the State-Trait-Error model was developed within an SEM framework, thereby allowing one to estimate and remove measurement error from the temporal data. This is as yet an infeasible option within the multilevel modeling framework.

We have shown that our model can be thought of as a place-holder for the influence of conceptually important factors on the covariance between examinee and partner anger. Thus, the same-day covariance between the anger scores of dyad members can be the result of shared daily experiences or of direct influence between the members. The covariance between the stable components of the anger scores, can, as Gonzalez and Griffin do, be thought of as a couple-level covariance. It might reflect a tendency for assortative mating based on tolerance/intolerance of anger or it could be the result of an environmental influence on both dyad members that is stable over time. An example of the latter might be high ambient noise levels that represent a chronic stressor on the dyad.

Our hope is that researchers interested in modeling dyadic processes can begin their analysis by estimating the covariance structure specified in our model and then by adding suitable predictors document the causal mechanisms that underlie that structure. Variations of our model could be developed that take account of the possibility that the autocorrelation process might be different on weekends than weekdays, or one partner's level of Y could have a lagged effect on the other partner's level at the next time point. In some applications, the model could be simplified. For example, if neither partner was facing an acute stressor it is conceivable that the partners might resemble exchangeable dyad rather than distinguishable members. Both approaches we have illustrated have some capacity to accommodate expanded models or constrained models. We hope relationship researchers will begin to use these methods to identify the processes underlying the substantial dependencies in longitudinal dyadic data.

Figure 1
Study Design: Diary Reports from Individuals in Two Roles Nested Within Sixty Five Couples Crossed with Seven Days

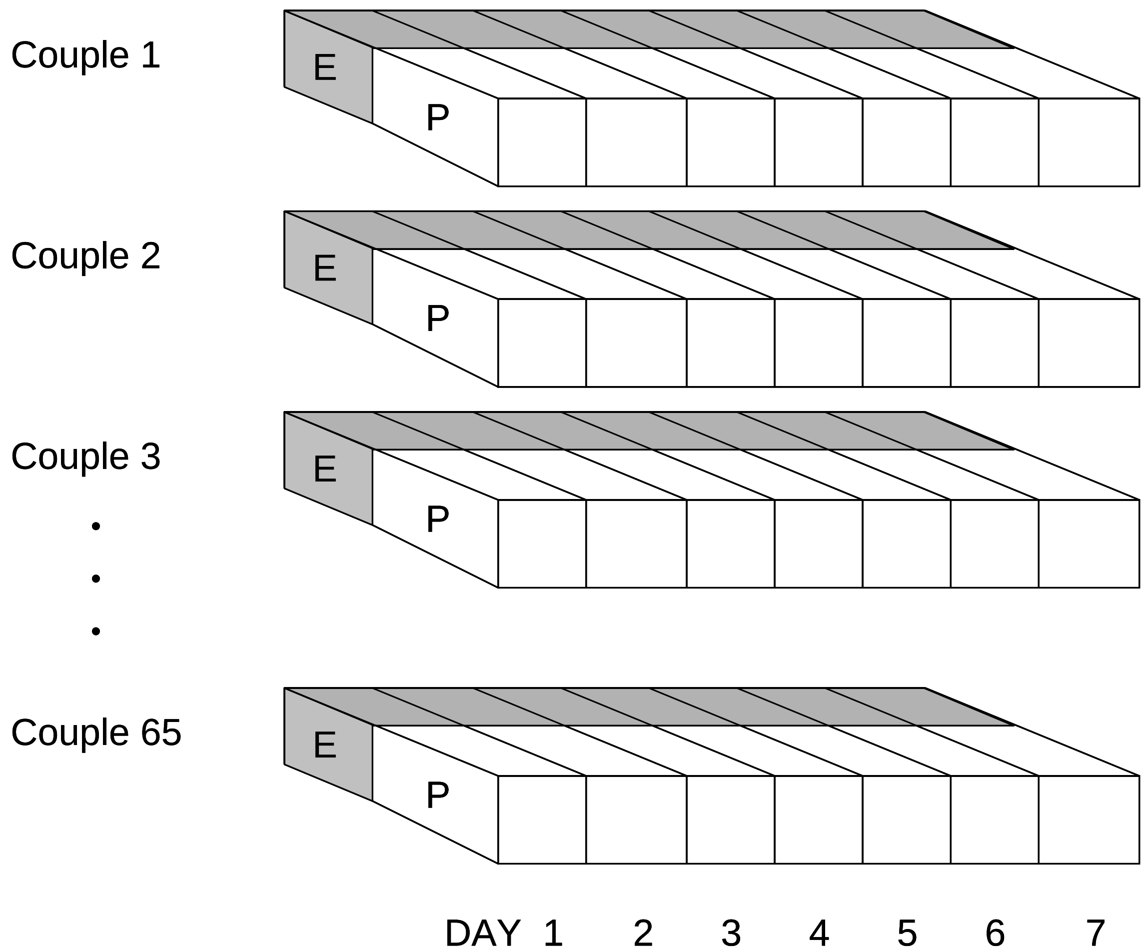

Figure 2: SEM Diagram for Dyadic Process Model

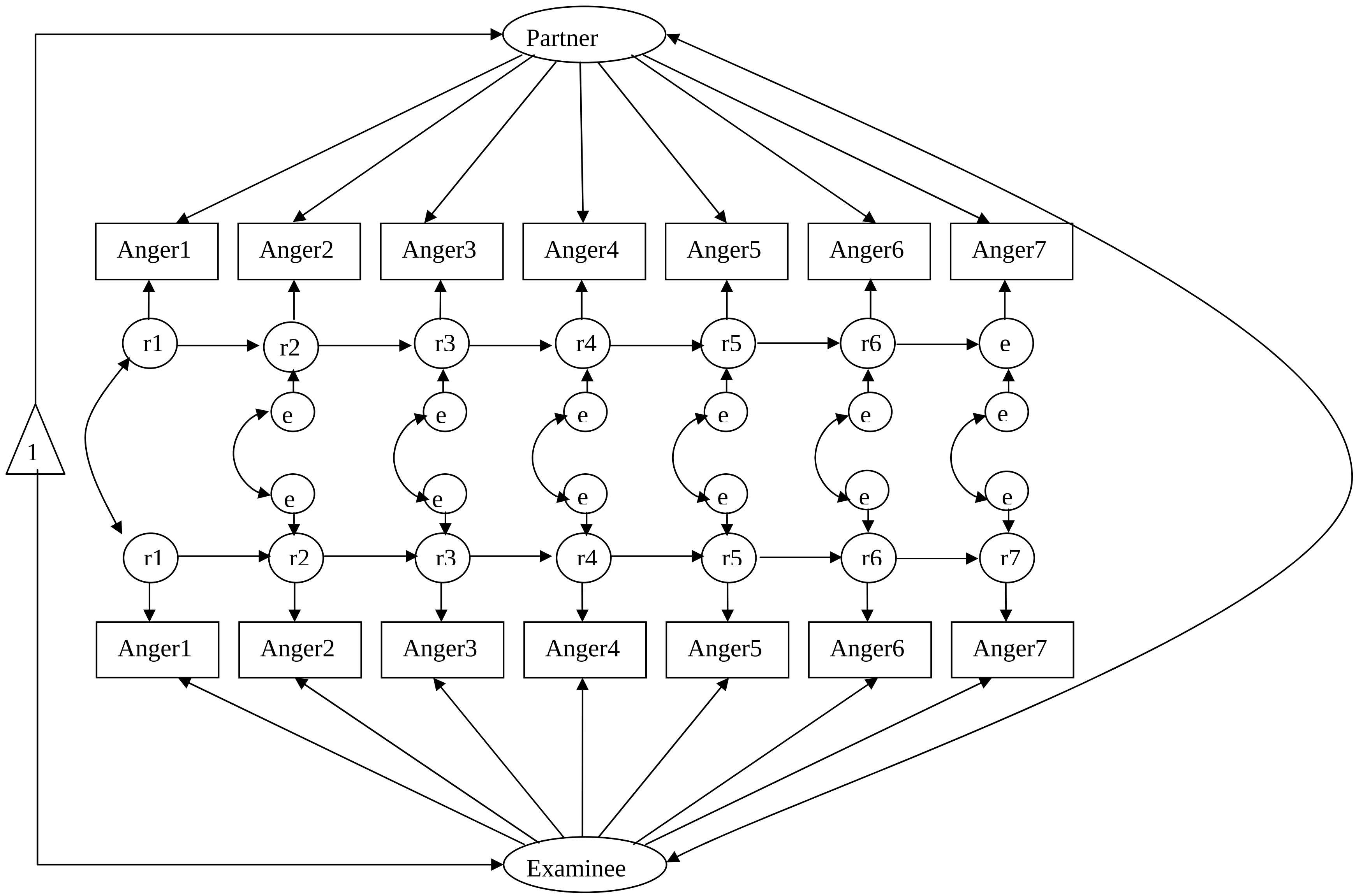

Table 1.
Correlations Among Seven Daily Reports of Examinee (E1, E2, …, E7) and Partner Anger (P1, P2, …, P7).

	Mean	SD	E1	E2	E3	E4	E5	E6	E7	P1	P2	P3	P4	P5	P6	P7
E1	0.664	0.813	1.00													
E2	0.621	0.914	0.42	1.00												
E3	0.520	0.573	0.23	0.55	1.00											
E4	0.570	0.840	0.04	0.21	0.40	1.00										
E5	0.426	0.580	0.18	0.27	0.31	0.54	1.00									
E6	0.435	0.556	0.16	0.01	0.16	0.43	0.42	1.00								
E7	0.488	0.580	0.11	0.14	0.20	0.38	0.27	0.45	1.00							
P1	0.727	0.801	**0.16**	0.07	0.06	-0.12	-0.08	-0.01	-0.06	1.00						
P2	0.836	0.944	0.19	**0.32**	0.30	0.04	0.11	0.09	0.24	0.37	1.00					
P3	0.645	0.905	-0.05	0.20	**0.25**	0.20	0.14	-0.07	-0.13	0.18	0.15	1.00				
P4	0.551	0.894	0.07	0.13	0.29	**0.57**	0.33	0.23	0.14	0.05	0.05	0.45	1.00			
P5	0.566	0.980	0.00	0.16	0.33	0.37	**0.38**	0.30	0.21	0.20	0.30	0.20	0.60	1.00		
P6	0.465	0.818	-0.17	0.02	0.17	0.35	0.26	**0.41**	0.34	0.06	0.20	0.08	0.33	0.66	1.00	
P7	0.523	0.711	-0.07	0.08	-0.01	0.21	0.04	0.09	**0.22**	0.18	0.24	0.11	0.34	0.49	0.43	1.00

Table 2

Parameter Estimates for Model Displayed in Figure 1

	Multilevel		SEM	
	Estimate	SE	Estimate	SE
Mean of Examinee Mean Anger	0.537	0.053	0.538	0.053
Mean of Partner Mean Anger	0.617	0.065	0.621	0.065
Variance of Examinee Mean Anger	0.080	0.035	0.088	0.034
Variance of Partner Mean Anger	0.116	0.053	0.118	0.051
Covariance of Examinee and Partner Mean Anger	0.045	0.031	0.050	0.030
Implied Correlation of Examinee and Partner Mean Anger	0.469		0.491	
Variance of Examinee Daily Anger Residuals	0.417	0.035	0.386	†
Variance of Partner Daily Anger Residuals	0.631	0.053	0.639	†
Covariance of Examinee and Partner Daily Anger Residuals	0.134	0.027	0.136	†
Implied Correlation of Examinee and Partner Daily Anger Residuals	0.262		0.274	
First-Order Autocorrelation of Daily Anger Residuals	0.316	0.046	0.296	0.047

† Values in these cells were computed rather than estimated directly, hence standard errors are not available.

Table 3
Model-Predicted Correlations as a Function of Time-Lag Based on Parameter Values in Table2

Day *t* with	Within examinee	Within Partner	Examinee-Partner
t	1.000	1.000	0.292
t-1	0.501	0.433	0.152
t-2	0.320	0.228	0.102
t-3	0.255	0.154	0.084
t-4	0.232	0.128	0.077
t-5	0.223	0.118	0.075
t-6	0.220	0.114	0.074

Appendix: Syntax for Estimating Parameters in Figure 1

Multilevel Model Approach: The MIXED Procedure of SAS

The multilevel approach uses a data set in which the records are person-days. On each record variables called, “couple” (couple number), “exmprt” (examinee vs. partner), “day”, indicate which kind of person and which day is represented on the record. Before the analysis is run, some new variables are created that contain the same information. The variable “daycl” is identical to “day”, but will used to define day as a class variable. The variable “exmnee” is a dummy code with 1 for examinee and 0 for partner. The variable “partner” is the complement of the latter: it is a dummy code with 1 for partner and 0 for examinee. With these variables one can use the following PROC MIXED syntax.

```
PROC MIXED DATA=anger COVTEST METHOD=REML;
 TITLE ‘Examinee and Partner random effects and correlated errors’;
 CLASS couple exmprt daycl ;
 MODEL anger=exmnee partner day / S NOINT;
 RANDOM exmnee partner / TYPE=UN G GCORR SUB=couple;
 REPEATED exmprt daycl / SUB=couple TYPE= UN@AR(1);
RUN;
```

Key features of this syntax are a) the specification of dummy codes, exmnee and partner, in the MODEL statement as distinct intercepts (note that NOINT suppresses the default intercept), b) the specification that the two intercepts are random in the RANDOM statement, and c) the specification of the Kronecker product structure for the residuals, TYPE= UN@AR(1), in the REPEATED statement.

Structural Equation Model Approach: EQS

The SEM approach uses data that are arranged as separate records for each couple. In EQS, these variables are called V1 to V14. The model requires 16 different latent variables, which are called F1 to F16. In the program below, F15 and F16 represent the random intercepts for examinee and partner, F1 and F8 represent the starting residual variances, and F2-F7, F9-F14 represent the autocorrelated residuals. The variances of F1 and F8 were fixed to values that were consistent with a stationary process.

```
/TITLE
SEM Model consistent with multilevel analysis
/SPECIFICATIONS
DATA='C:\Pat\Couples\Analyses\SPSP04\foreqs.ess';
VARIABLES=14; CASES=64;
METHOD=ML; ANALYSIS=MOMENT; MATRIX=RAW;
/LABELS
V1=EXM1; V2=EXM2; V3=EXM3; V4=EXM4; V5=EXM5;
V6=EXM6; V7=EXM7; V8=PRT1; V9=PRT2; V10=PRT3;
V11=PRT4; V12=PRT5; V13=PRT6; V14=PRT7;
/EQUATIONS
V1 =  + 1F1  + 1F15  ;
V2 =  + 1F2  + 1F15  ;
V3 =  + 1F3  + 1F15  ;
V4 =  + 1F4  + 1F15  ;
V5 =  + 1F5  + 1F15  ;
V6 =  + 1F6  + 1F15  ;
V7 =  + 1F7  + 1F15  ;
V8 =  + 1F8  + 1F16  ;
V9 =  + 1F9  + 1F16  ;
V10 =  + 1F10 + 1F16  ;
V11 =  + 1F11 + 1F16  ;
V12 =  + 1F12 + 1F16  ;
V13 =  + 1F13 + 1F16  ;
V14 =  + 1F14 + 1F16  ;
F2 =  + *F1  + D2;
F3 =  + *F2  + D3;
F4 =  + *F3  + D4;
F5 =  + *F4  + D5;
F6 =  + *F5  + D6;
F7 =  + *F6  + D7;
F9 =  + *F8  + D9;
F10 =  + *F9  + D10;
F11 =  + *F10  + D11;
F12 =  + *F11  + D12;
F13 =  + *F12  + D13;
F14 =  + *F13  + D14;
F15 =  *V999 + D15;
F16 =  *V999 + D16;
/VARIANCES
V999= 1;
F1 = .386; F8 = .639;
D2 = *; D3 = *; D4 = *; D5 = *; D6 = *; D7 = *;
D9 = *; D10 = *; D11 = *; D12 = *; D13 = *; D14 = *;
D15 = *; D16 = *;
/COVARIANCES
D16, D15 = *;
```

```
F1,F8=*;
D2,D9=*; D3,D10=*; D4,D11=*; D5,D12=*; D6,D13=*; D7,D14=*;
/CONSTRAINTS
(D2,D2)=(D3,D3)=(D4,D4)=(D5,D5)=(D6,D6)=(D7,D7);
(D9,D9)=(D10,D10)=(D11,D11)=(D12,D12)=(D13,D13)=(D14,D14);
(F2,F1)=(F3,F2) =(F4,F3)  =(F5,F4)  =(F6,F5)  =(F7,F6);
(F9,F8)=(F10,F9)=(F11,F10)=(F12,F11)=(F13,F12)=(F14,F13);
(D2,D9)=(D3,D10)=(D4,D11)=(D5,D12)=(D6,D13)=(D7,D14);
(F2,F1)=(F9,F8);
/PRINT
FIT=ALL;
TABLE=EQUATION;
COVARIANCE=YES;
/END
```

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Notes

[1] We are able to apply these simplifying assumptions to the residual covariance matrix using options in the MIXED procedure of the SAS system. There is a REPEATED section in the syntax that allows specification of correlated residuals, and one option is TYPE=UN@AR(1). This coding refers to a Kronecker Product (e.g. see Bock, 1974) of a 2 by 2 covariance matrix for persons within couple, and of a 7 by 7 correlation matrix with the lag 1 autoregression pattern.

[2] The multilevel model fits the overall structure of the residual variance covariance matrix without decomposing the variance into autoregressive and random shock influences, in contrast to the SEM approach. Moreover, the multilevel model assumes that the autoregressive process on the residuals is stationary, which means that the variance of the residual is equal to the variance of the random shocks divided by ($1-\rho^2$), where ρ^2 is the squared autocorrelation. This constraint cannot be readily imposed in EQS, but we approximated the restraint by iteratively estimating the autocorrelation and random shock variance and fixing the initial residual variances to these derived values.

[3] As the exam draws closer in time, examinees begin to report higher levels of anger than their partners.

[4] It might seem unintuitive that an unbiased estimate of a correlation is less precise than bias estimate. However, these characteristics of estimators are completely distinct (see Welsh (1996) for other examples). In our case, the adjustment of the correlation for measurement error depends on estimates of the error-free variances of the latent variables, and the uncertainty of these estimates leads to imprecision of the correlation estimate.