Karen S. Lyons *Oregon Health & Science University*

Aline G. Sayer *University of Massachusetts at Amherst**

Longitudinal Dyad Models in Family Research

Multilevel modeling allows for the simultaneous analysis of data gathered at more than 1 unit of analysis (e.g., children nested in schools). It is often used to examine the effects of various contexts on individual differences in change. This paper promotes the application of multilevel models to longitudinal dyadic data in family research. By focusing on the dyad as context, researchers can examine within-dyad change and begin to understand the interactive processes that constitute the relationship between partners. They can then frame questions about interdyad differences in within-dyad change. We present several longitudinal models that researchers can use to examine the pattern of change within dyads, assess heterogeneity in change across dyads, and investigate cross-partner effects on change. We comment on the implications of these models for family research.

Multilevel modeling is a methodology that allows for the simultaneous analysis of data gathered at more than one unit of analysis (e.g., children in schools, individuals in families, repeated assessments in individuals). Multilevel modeling allows the researcher to examine the effects of various contexts and systems on individual change, whether the context is construed as a neighborhood, a school, a family, or a dyad. As such, multilevel modeling is a complementary methodology to the many family theories interested in nested data and cross-level effects and has received growing attention in the field (e.g., a special section in the *Journal of Marriage and Family*, May 2002). The purpose of this paper is to promote the application of multilevel models to longitudinal dyadic data in family research.

Multilevel Modeling and Family Research

Multilevel modeling has been used by family researchers to examine individual-level change including growth in children's problem behaviors (Hussey & Guo, 2003) and health declines in spouses of individuals with Parkinson's disease (Lyons, Stewart, Archbold, Carter, & Perrin, 2004). It has also been applied to investigate contextual issues such as the effect of family structure on adolescent drug use (Hoffmann, 2002) and community effects on parenting strategies (Simons et al., 2002). Family theories also emphasize family as a context for development through examining the interactions and relationships among family members (e.g., Bronfenbrenner's Ecological Systems Theory, Minuchin's Family Systems Theory). Recently, family researchers have adapted multilevel modeling to examine the context of a particular family relationship, the marital dyad (e.g., Bost, Cox, & Payne, 2002; Davey & Szinovacz, 2004; Klute, Crouter, Sayer, &

School of Nursing, Oregon Health & Science University, 3455 SW U.S. Veterans Road, SN-ORD, Portland, OR 97239 (Lyonsk@ohsu.edu).

*Psychology Department, Tobin Hall, 135 Hicks Way, University of Massachusetts at Amherst, Amherst, MA 01003-9271.

Key Words: dyadic data, hierarchical linear models, longitudinal research, multilevel models.

McHale, 2002). Multilevel modeling in dyadic research permits the study of individual outcomes such as depression and health within the context of the dyadic relationship while controlling for the interdependency of scores among dyad members. In addition, the effects of dyadic characteristics such as marital satisfaction or conflict, whether measured by individual partner perceptions or third-party observations, on individual outcomes can be assessed. By focusing on the dyad as the unit of analysis, family researchers can examine the relational character of change within dyads and begin to understand the interactive dynamic processes that constitute the relationship (Thompson & Walker, 1982).

What types of research questions can be posed using multilevel modeling? Family researchers interested in the influence of chronic illness on married couples often ask questions at both the individual level and the couple level of analysis. Individual-level questions might ask whether individuals who openly discuss disease symptoms or disease progression are more likely to have greater intimacy with their partner. Couple-level questions might ask whether couples who are more emotionally congruent are more likely to agree about the occurrence of symptoms. Similarly, multilevel modeling allows the researcher to answer questions regarding cross-partner effects (e.g., are changes in husband depression associated with changes in wife anger regarding her breast cancer?) and the differential effects of interventions at the individual (e.g., does one member of the dyad fare better than the other?) and couple level (e.g., does the intervention increase emotional congruence in the dyad?). We emphasize that multilevel modeling can address these and similar questions not only cross-sectionally but also longitudinally. We can pose questions regarding dyadic change over time, for example, as the disease progresses, do partners become more or less congruent?

When used to examine organizational effects (e.g., schools on children), multilevel modeling assumes that all lower level units (i.e., children) nested within the same upper level unit (i.e., school) are interchangeable. For the models we present here, we assume that partners are not interchangeable but can be distinguished from one another on the basis of some status such as marital role of husband and wife, family role of brother and sister, or care role of patient and care provider (see Gonzalez & Griffin, 1997; Kurdek, 2003). When the multilevel model is written as a multivariate hierarchical linear model, two dummy variables are included in the Level 1 model to capture the distinction in role. Barnett, Marshall, Raudenbush, and Brennan (1993) used a version of this model to examine gender differences in the relationship between job quality and psychological distress for 300 dual-earner couples. They parameterized the model at Level 1 to include two indicator variables, one for each partner. The coefficients associated with these variables become separate outcomes in the Level 2 model that have been adjusted for both measurement error and the correlation between the couple outcome scores within each dyad. This model took advantage of the matched-pairs design by including as predictors variables measured on both the individual and the couple. The effects of these variables can often be confounded, for example, individual and household income. For example, traditional methodologies used in marital research examine men and women separately, either ignoring the partnership or using samples of nonpartnered people. Such methodologies may misinterpret differences resulting from couple-level characteristics such as household income as gender differences. The ability to examine the effects of both individual- and dyad-level variables is an important advantage of the multivariate outcomes model for dyads.

Advantages of Multilevel Modeling

Multilevel modeling for dyads extends multiple regression to the case where the responses of the members of the dyad are conceived as Level 1 units nested within the Level 2 unit, the dyad. The model can be adapted to represent a cross-sectional model for matched pairs (Barnett et al., 1993) in which the dyad replaces the individual as the unit of analysis. The model described by Raudenbush, Brennan, and Barnett (1995) is an amalgam of the cross-sectional model for matched pairs and the longitudinal model for individual change. The longitudinal matched-pairs model is fit to the repeated assessments of the outcome variables for both members and compares patterns of change in trajectories for both partners. This multivariate model estimates a latent trajectory for each member of the dyad that can differ in pattern and magnitude across partners.

We refer the interested reader to Sayer and Klute (2005) for a discussion of the advantages of using multilevel modeling for analyzing cross-sectional dyads, including a comparison with more traditional methods such as single-partner assessments, sum scores, deviation scores, and analysis of variance. Here, we point out the additional advantages of using multilevel modeling when estimating longitudinal trajectory models for dyads. From a design standpoint, the major within-dyad advantage is that each partner can have a unique trajectory. The trajectories can be specified to differ in pattern (i.e., change can be linear for wives and nonlinear for husbands) and magnitude (i.e., the rate of change can be steeply negative for wives and flat for husbands). Multilevel modeling allows the incongruence of the average trajectories for each partner to be directly tested for significant differences at the intercept (the predicted score at a specific occasion of measurement), the slope (rate of change), or both using a generalized multivariate hypothesis test. This is not possible when trajectories are estimated in separate models. A second advantage of this model is that it controls for the autocorrelation among the repeated measures as well as adjusting the error variance for the interdependence of partner outcomes within the same dyad. This adjustment results in more accurate standard errors and their associated hypothesis tests. A third advantage of the model is that it allows for unbalanced designs: There can be differences in both the number and spacing of the times of measurement across dyads. A fourth advantage is that it allows for missing responses under the assumption that the data are missing at random. It is possible for only one member of the dyad to contribute data or for the pattern of missing responses to be different for each partner.

Although it has been 10 years since Barnett et al. (1993) and Teachman, Carver, and Day (1995) described multilevel dyad models, they are still not widely adopted by family and marital researchers. Among researchers who have used them, the emphasis has primarily been on understanding gender differences in marital dyads (Klute et al., 2002; Raudenbush et al., 1995; Townsend, Miller, & Guo, 2001), actor-partner effects in small groups (Kenny, 1996; Rayens & Svavarsdottir, 2003), and cross-spouse effects in retired couples (Davey, Fincham, Beach, & Brody, 2001). We have used a variety of ways to parameterize the model initially described by Barnett et al. These include a cross-sectional discrepancy model that examined dyad discrepancy in barriers to care and physical dependence in a sample of 63 care dyads (Lyons, Zarit, Sayer, & Whitlatch, 2002), a cross-sectional multivariate outcomes model that examined gender differences in parenting stress (Sayer & Klute, 2005) in a sample of 51 couples of children with disabilities, and a longitudinal multivariate outcomes model that examined the relationship between changes in job quality and changes in psychological distress over 3 years for 210 dual-earner couples (Barnett, Raudenbush, Brennan, Pleck, & Marshall, 1995). The present methodological paper extends this work by focusing on longitudinal dyad models and moves beyond the marital dyad to examine change in another important family relationship, the family care relationship.

THE LONGITUDINAL MULTIVARIATE OUTCOMES MODEL

The multivariate outcomes model described by Raudenbush et al. (1995) is an amalgam of the cross-sectional model for matched pairs and the longitudinal model for individual change. It is fit to the repeated assessments of the outcome for both partners in the dyad and, as noted previously, provides estimates of the average partner trajectories as well as the heterogeneity across dyads around the average trajectories. It differs from analyses on separate samples of partners by fitting the equations simultaneously and controlling for within-dyad dependence of observations.

Level 1 Model: Within-Dyad Model

The Level 1 or within-dyad model represents the repeated measures for both dyad members as functions of time (in this case, linear and quadratic), plus a residual term r that captures measurement error, or the time-specific error of prediction. The variance of these measurement errors is considered to be constant both within and across dyads. For care dyads consisting of a frail older person and a family member providing care, the model is written as follows:

$$\begin{aligned} Y_{tp} = & (\mathrm{OP})\left[\beta_{1p} + \beta_{2p}(\mathrm{LIN}_{tp}) + \beta_{3p}(\mathrm{QUAD}_{tp})\right] \\ & + (\mathrm{FM})\left[\beta_{4p} + \beta_{5p}(\mathrm{LIN}_{tp}) \right. \\ & \left. + \beta_{6p}(\mathrm{QUAD}_{tp})\right] + r_{tp}, \end{aligned} \quad (1)$$

where Y_{tp} represents the outcome score Y ($t = 1, \ldots K$ responses per dyad and time of measurement) for dyad p. OP is an indicator variable taking on a value of 1 if the response was obtained from an older person and 0 if the response was obtained from a family member providing care. FM is an indicator variable taking on a value of 1 if the response was obtained from a family member providing care and 0 if the response was obtained from an older person. The brackets indicate that the coefficients and variables are multiplied by the respective indicator variable. Therefore, the first set of brackets contains the latent growth parameters β_{1p}, β_{2p}, and β_{3p} (intercept, linear component, quadratic component) characterizing the trajectory for the older person; the second set contains the latent growth parameters β_{4p}, β_{5p}, and β_{6p} characterizing the trajectory for the family member. Thus, each dyad has six coefficients (β_{1p}, β_{2p}, β_{3p}, β_{4p}, β_{5p}, and β_{6p}) that represent the true growth parameters for the dyad. The r_{tp} are the within-dyad residuals, also called the Level 1 random effects. They are assumed to be normally distributed, with a mean of 0 and variance σ^2.

We note that the assumption of constant variance σ^2 is likely to be untenable in the repeated measures case and should be evaluated with a test of homogeneity of variance. The conventional way to test this assumption is to fit a model with an alternative structure for the Level 1 error component, for example, heterogeneous variance that allows for estimation of a different variance at each time point. A likelihood ratio test that compares the deviance statistic of the alternative model against the fit of the more restrictive model (i.e., homogeneous variance) allows the researcher to evaluate the tenability of the assumption of constant variance. If the alternative model provides a significantly better fit to the data, researchers should use this model in all further analyses to avoid misspecification of the Level 1 model (Raudenbush & Bryk, 2002).

Unconditional Level 2 Model: Between-Dyad Model

The Level 1 coefficients serve as outcomes at Level 2. They are permitted to vary across all Level 2 units (dyads) and can take on different values for each dyad. The first step in any longitudinal analysis is to fit an unconditional model or a model that does not include any predictor variable at Level 2. It is specified as follows:

$$\beta_{1p} = \gamma_{10} + u_{1p} \tag{2}$$

$$\beta_{2p} = \gamma_{20} + u_{2p} \tag{3}$$

$$\beta_{3p} = \gamma_{30} + u_{3p} \tag{4}$$

$$\beta_{4p} = \gamma_{40} + u_{4p} \tag{5}$$

$$\beta_{5p} = \gamma_{50} + u_{5p} \tag{6}$$

$$\beta_{6p} = \gamma_{60} + u_{6p} \tag{7}$$

The *unconditional* between-dyad model provides estimates of the population averages for each growth parameter for the older person (γ_{10}, γ_{20}, and γ_{30}) and for the family member (γ_{40}, γ_{50}, and γ_{60}). These estimates are known as the fixed effects in the model, and they represent the means of the distribution of the respective coefficients across dyads. The Level 2 random effects u_{1p}, u_{2p}, u_{3p}, u_{4p}, u_{5p}, and u_{6p} represent the deviation of each dyad from the respective population average growth parameter. The variances of these random effects (τ_{00}, τ_{11}, τ_{22}, τ_{44}, τ_{55}, τ_{66}) can be estimated and represent the heterogeneity across dyads. It is possible to test whether each variance is significantly different from zero in the population. If any are, significant variability exists across dyads, and predictors can be introduced to explain this variability.

Conditional Level 2 Model: Between-Dyad Model

The conditional Level 2 model introduces predictors to explain the variance in the trajectories across dyads. The predictors can be variables with common values for each dyad member (e.g., the family member in the dyad can be a spouse or an adult child) or those with unique values for each partner (e.g., mental health). It is specified as follows:

$$\beta_{1p} = \gamma_{10} + [\gamma_{11}\ \text{Predictor}_1 + \ldots \gamma_{1n}\ \text{Predictor}_n] + u_{1p} \tag{8}$$

$$\beta_{2p} = \gamma_{20} + [\gamma_{21}\ \text{Predictor}_1 + \ldots \gamma_{2n}\ \text{Predictor}_n] + u_{2p} \tag{9}$$

$$\beta_{3p} = \gamma_{30} + [\gamma_{31}\ \text{Predictor}_1 + \ldots \gamma_{3n}\ \text{Predictor}_n] + u_{3p} \tag{10}$$

$$\beta_{4p} = \gamma_{40} + [\gamma_{41}\ \text{Predictor}_1 + \ldots \gamma_{4n}\ \text{Predictor}_n] + u_{4p} \quad (11)$$

$$\beta_{5p} = \gamma_{50} + [\gamma_{51}\ \text{Predictor}_1 + \ldots \gamma_{5n}\ \text{Predictor}_n] + u_{5p} \quad (12)$$

$$\beta_{6p} = \gamma_{60} + [\gamma_{61}\ \text{Predictor}_1 + \ldots \gamma_{6n}\ \text{Predictor}_n] + u_{6p} \quad (13)$$

The *conditional* between-dyad model provides estimates of the population averages for each growth parameter for the older person (γ_{10}, γ_{20}, and γ_{30}) and for the family member (γ_{40}, γ_{50}, and γ_{60}) adjusted for the effects of the predictors in each equation. The fixed effects of each predictor are captured by the respective regression coefficient γ and represent the relationship between each predictor and the respective growth parameter. The Level 2 random effects u_{1p}, u_{2p}, u_{3p}, u_{4p}, u_{5p}, and u_{6p} now represent the conditional deviation of each dyad from the respective population average growth parameter or the unexplained residual variance in each parameter.

Data Example

The above models are illustrated using three waves of data from 74 care dyads drawn from a larger study in a northwestern U.S. city. Care dyads consisted of a frail older person in receipt of standard home health and a family member providing care to that older person. Thus, the members of the care dyad have distinguishable roles. For this paper, we examine the effect of the family member's mental health and type of dyad relationship (marital, where the family member was a spouse, or parent-child, where the family member was an adult child) on change in the positive quality of the care relationship (mutuality).

The variable *mutuality* is measured by a 15-item scale developed by Archbold and Stewart. Both the older person and family member respond to items about their relationship with each other, using a Likert scale anchored at 0 (*not at all*) and 4 (*a great deal*). Individuals receiving high scores on this scale report that their relationship with the other is characterized by reciprocity, love, pleasurable activities, and shared values, whereas individuals receiving low scores report that their relationship with the other is not characterized by these qualities. The Mutuality Scale has exhibited high Cronbach's alpha values (.91–.95) in studies of family care (Archbold, Stewart, Greenlick, & Harvath, 1990; Carter et al., 1998). The Mutuality Scale was administered three times at 5-month intervals.

Family member's mental health is measured at baseline using the mental component summary score from the Medical Outcomes Study 36 Item Short Form Health Survey (Ware & Gandek, 1998). Higher numbers indicate better mental health (range of 0–100). The summary scale has undergone extensive psychometric testing and demonstrated good reliability and validity (Kane & Kane, 2000; Ware & Gandek). Type of family dyad is coded 1 for *marital dyads* and 0 for *parent-child dyads*. Marital dyads made up 57% of the sample of dyads presented here.

Results

Level 1 Model: Within-Dyad Model

A number of computer programs are available to fit the multilevel model, including MLwiN, LISREL, SAS PROC MIXED, and HLM. We used maximum likelihood via the HLM6 program of Raudenbush, Bryk, and Congdon (2004) to estimate the parameters of the Level 1 and Level 2 models.

In a traditional individual growth curve model, it is customary to estimate a trajectory with one fewer the number of model coefficients than waves of data. The additional degree of freedom is required to estimate the within-subject measurement error variance (Barnett et al., 1993; Raudenbush et al., 1995). In a multivariate dyad model, there are alternative approaches to estimating this measurement error variance if the researcher wants to fit a model with as many parameters as occasions of measurement. In our example, we wanted to estimate a model with three coefficients (either a quadratic model or a linear model that includes a time-varying covariate) to three waves of data. The first strategy involves weighting the outcome by its reliability. The researcher provides information to the program about the measurement error variance (obtained from sources external to the program), and the program then computes a precision weight (the inverse of the measurement error) in order to weight the outcomes by their reliability. A weighted analysis is carried out rather than have the program estimate the error variance from the data, thus saving a degree of freedom. The second method involves the creation of two parallel scales for each member of the dyad for each wave of data, an approach originally suggested by Barnett et al. First, item pairs are formed by matching the items on their standard deviations. Then, one item from each pair is randomly assigned to Scale A and the other to Scale B. This procedure results in two parallel scales approximately equal in reliability and variance. The additional information provided by the parallel scales permits the program to estimate the measurement error variance.

An example of the data structure for one dyad using the parallel-scales approach is shown in Table 1. We created two scales using seven items each. Thus, there were 12 observations for a dyad with complete data, Mutuality Scale A and Mutuality Scale B, for each of three waves, for each member of the dyad.

Table 1 is the data record for the first dyad. The first column contains the dyad's ID number. The second column contains the outcome (mutuality score) with two responses at each time point representing the scores on the two parallel scales. The third and fourth columns contain two dummy variables that represent Older Person and Family Member. If Older Person takes on a value of 1, it denotes that the mutuality response was contributed by that member of the dyad. If Family Member takes on a value of 1, it denotes that the mutuality response was assessed on the family member. We note that the first six mutuality values are assessed on the older person and the last six on the family member. The fifth and sixth columns are labeled Older Person Linear and Family Member Linear and denote the linear time values for both the older person and family member. Typically, the original recorded value of time is rescaled in multilevel modeling to facilitate interpretation of the intercept in the trajectory. The intercept is the predicted value of the outcome when time is equal to 0 or at the origin. By subtracting a known constant from the original time values, we can give a substantively meaningful value to the intercept. The decision on where to place the origin has important implications for interpretation of the growth curve trajectory parameters and should be weighed carefully. (For a fuller discussion of this topic, see Biesanz, Deeb-Sossa, Papadakis, Bollen, & Curran, 2004.) In this example, we subtracted 1 from each time value so that the intercept (when time is equal to 0) is at the initial or baseline assessment. The value 1 indicates the next occasion of measurement, which occurred 5 months after the onset of the study, and the value 2 indicates the final assessment point, which occurred 10 months after study inception. Thus, a one-unit change in time represents a 5-month interval. Finally, the seventh and eighth columns are labeled Older Person Quadratic and Family Member Quadratic and denote the quadratic values for both the older person and family member, which are computed by squaring the linear values.

TABLE 1. LEVEL 1 RECORD FOR ONE CARE DYAD

Care Dyad ID	Mutuality	Older Person	Family Member	Older Person Linear	Family Member Linear	Older Person Quadratic	Family Member Quadratic
513	3.14	1	0	0	0	0	0
513	3.00	1	0	0	0	0	0
513	3.14	1	0	1	0	1	0
513	3.00	1	0	1	0	1	0
513	3.43	1	0	2	0	4	0
513	3.43	1	0	2	0	4	0
513	2.00	0	1	0	0	0	0
513	2.57	0	1	0	0	0	0
513	2.00	0	1	0	1	0	1
513	2.14	0	1	0	1	0	1
513	2.57	0	1	0	2	0	4
513	2.86	0	1	0	2	0	4

The underlying form of change for many social phenomena is often unknown. Theory and previous research can sometimes shed light on the expected pattern of change, but typically an empirical approach is taken by estimating competing models (e.g., linear and quadratic) and comparing the fit to the data. Previous research consistently shows that mutuality declines over time (e.g., Aneshensel, Pearlin, Mullan, Zarit, & Whitlatch, 1995; Carter & Nutt, 1998; Carter et al., 1998), but whether the pattern of decline is linear or curvilinear is not known. We estimated both a linear model and a quadratic model and compared their deviance statistics. The change in the deviance statistic is distributed as χ^2 and can be tested relative to the change in the degrees of freedom. We found the quadratic model to be a significantly better fit to the data ($\chi^2 = 65.74$, $df = 13$, $p < .001$).

Unconditional Level 2 Model: Between-Dyad Model

Fixed effects. Columns 1 through 4 of Table 2 present the maximum likelihood estimates of the fixed effects and their associated standard errors for the unconditional model. Older persons rated mutuality higher at baseline compared to family members ($\gamma_{10} = 3.46$ vs. $\gamma_{40} = 2.97$). There was evidence of a significant negative linear slope for family members over the 10-month period ($\gamma_{50} = -0.17$, $p < .05$). There was no significant linear trend for older persons ($\gamma_{20} = -0.07$, $p > .05$) nor were the mean quadratic effects significantly different from zero for either care partner.

A multivariate hypothesis test revealed a significant difference between the average trajectories for older persons and family members ($\chi^2 = 41.03$, $df = 3$, $p < .001$). The trajectories are plotted in Figure 1.

Random effects. Columns 1 through 6 of Table 3 contain estimates of the variance components for the unconditional model.

The associated χ^2 tests indicated that for each component, we reject the null hypothesis that the variance is zero in the population. There is significant heterogeneity around the average score for all growth parameters (intercept, linear slope, and quadratic slope) for both members of the dyad.

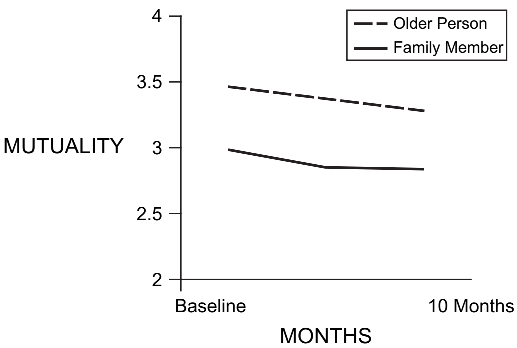
Our unconditional model provides estimates of the reliabilities of each growth parameter (for older persons, intercept = .87, linear component = .70, and quadratic component = .70; for family members, the respective estimates were

TABLE 2. MULTILEVEL MODEL FIXED-EFFECT RESULTS PREDICTING OLDER PERSONS' AND FAMILY MEMBERS' MUTUALITY OVER TIME FROM DYAD TYPE AND FAMILY MEMBERS' MENTAL HEALTH AT BASELINE USING FULL MAXIMUM LIKELIHOOD ESTIMATION ($N = 74$ DYADS)

	Unconditional Model				Conditional Model			
	Older Persons		Family Members		Older Persons		Family Members	
Model	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Intercept	3.46***	0.06	2.97***	0.08	3.54***	0.09	2.72***	0.11
Dyad type[a]					−0.14	0.12	0.43**	0.16
Family member mental health[b]					0.01*	0.00	0.01*	0.00
Linear slope	−0.07	0.10	−0.17*	0.08	−0.17	0.16	−0.32**	0.12
Dyad type					0.18	0.22	0.26	0.17
Family member mental health					−0.01	0.01	−0.01	0.01
Quadratic slope	−0.01	0.05	0.05	0.04	0.02	0.08	0.11	0.07
Dyad type					−0.04	0.11	−0.11	0.08
Family member mental health					0.01	0.01	−0.01	0.02
Estimated parameters	28				40			
Deviance statistic	757.26				719.79			
χ^2					37.47**			

Note: Unstandardized coefficients are shown.
[a]1 = *marital dyad* and 0 = *adult child–parent dyad.* [b]Lower numbers reflect poorer mental health.
*$p < .05$. **$p < .01$. ***$p < .001$.

FIGURE 1. AVERAGE MUTUALITY TRAJECTORIES FOR OLDER PERSONS AND FAMILY MEMBERS OVER 10-MONTH PERIOD ($N = 74$ DYADS). HIGHER SCORES INDICATE GREATER MUTUALITY WITH A POSSIBLE RANGE OF 0–4.



.94, .51, and .54). These reliabilities can be thought of as a signal-to-noise ratio and represent the degree of systematic variance in each parameter. The reliability estimates are quite high and will boost our power to detect associations between selected predictors and growth in mutuality. The reliability estimates are closely related to the variance within and between dyads. For instance, by estimating an intercept-only model, we can estimate the proportion of the variance between dyads. This is given by the intraclass correlation $\rho = \tau_{00}/(\tau_{00} + \sigma^2)$, where τ_{00} is the variance in average mutuality (pooled across the three occasions of measurement) and σ^2 is the Level 1 sampling variance. In our example, the estimate of the intraclass correlation is 63%, indicating that there is more variation between dyads than within dyads. To determine the reliability estimates for the intercept, the intraclass correlation is adjusted for dyad size using the formula $\lambda_j = \tau_{00}/[\tau_{00} + (\sigma^2/nj)]$, where nj represents the number of responses within each dyad. Averaging across the reliabilities estimated for each dyad provides a summary of reliability for each growth parameter estimate for the sample of dyads. Reliability estimates are close to 1 when the parameter intercepts vary substantially across dyads (Raudenbush & Bryk, 2002). We note that the reliability formula is adjusted for the number and spacing of the waves of data when estimating the reliability of the slope and quadratic parameters rather than for the number of responses per dyad.

Table 4 presents the matrix of correlations among the Level 2 random effects, the variance components. The variances (and covariances) of the coefficients that constitute the growth trajectories can be obtained from the unconditional model, where the residual variance is interpreted as the degree of heterogeneity around the average growth parameter. Notable correlations are those that represent the extent of shared variance in the outcomes for members of the dyad. The correlation between older person and family member is .34 for the intercept, −.13 for linear change, and −.18 for quadratic change. These estimates indicate moderate shared variance and provide support for our decision to use a multilevel model.

Conditional Level 2 Model: Explaining Variation in Growth Parameters

A conditional model adds predictors at Level 2 to explain the heterogeneity in change across dyads. A conditional model that includes the predictors for type of dyad (DYADTYPE)

TABLE 3. MULTILEVEL MODEL RANDOM-EFFECT RESULTS FOR UNCONDITIONAL AND CONDITIONAL LEVEL 2 MODELS USING FULL MAXIMUM LIKELIHOOD ESTIMATION ($N = 74$ DYADS)

	Unconditional Model						Conditional Model					
	Older Persons			Family Members			Older Persons			Family Members		
Model	Variance Component	*df*	χ^2	Variance Component	*df*	χ^2	Variance Component	*df*	χ^2	Variance Component	*df*	χ^2
Intercept	0.21	50	294.6***	0.48	50	834.7***	0.19	48	270.2***	0.36	48	712.3***
Linear slope	0.49	50	153.4***	0.20	50	112.5***	0.44	48	151.8***	0.18	48	109.1***
Quadratic slope	0.11	50	170.9***	0.05	50	115.9***	0.11	48	171.6***	0.05	48	112.9***
Level 1 residual	0.06						0.06					

$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

TABLE 4. MULTILEVEL MODEL RANDOM-EFFECT RESULTS FOR UNCONDITIONAL MODEL: TAU CORRELATIONS ($N = 74$ DYADS)

Variables	1	2	3	4	5	6
1. Family member intercept	—					
2. Older person intercept	.34	—				
3. Family member linear slope	−.13	.33	—			
4. Older person linear slope	−.25	−.30	−.13	—		
5. Family member quadratic slope	.07	−.33	−.94	.17	—	
6. Older person quadratic slope	.25	.16	.19	−.91	−.18	—

Note: As standard errors are not estimated for these correlations, they are interpreted in a descriptive manner.

and family member's mental health (FM-MENTALHLTH) takes the following form:

$$\beta_{1p} = \gamma_{10} + \gamma_{11}\ \text{DYADTYPE}_p + \gamma_{12}\ \text{FM-MENTALHLTH}_p + u_{1p} \quad (14)$$

$$\beta_{2p} = \gamma_{20} + \gamma_{21}\ \text{DYADTYPE}_p + \gamma_{22}\ \text{FM-MENTALHLTH}_p + u_{2p} \quad (15)$$

$$\beta_{3p} = \gamma_{30} + \gamma_{31}\ \text{DYADTYPE}_p + \gamma_{32}\ \text{FM-MENTALHLTH}_p + u_{3p} \quad (16)$$

$$\beta_{4p} = \gamma_{40} + \gamma_{41}\ \text{DYADTYPE}_p + \gamma_{42}\ \text{FM-MENTALHLTH}_p + u_{4p} \quad (17)$$

$$\beta_{5p} = \gamma_{50} + \gamma_{51}\ \text{DYADTYPE}_p + \gamma_{52}\ \text{FM-MENTALHLTH}_p + u_{5p} \quad (18)$$

$$\beta_{6p} = \gamma_{60} + \gamma_{61}\ \text{DYADTYPE}_p + \gamma_{62}\ \text{FM-MENTALHLTH}_p + u_{6p} \quad (19)$$

In this model, the effect of family member's baseline mental health is captured by the coefficients γ_{12}, γ_{22}, γ_{32}, γ_{42}, γ_{52}, and γ_{62}, controlling for the effect of type of dyad. This model includes variables with common values for both members of the dyad (type of family dyad) and specific to the family member (family member's mental health). It also examines a cross-care partner effect represented by γ_{12}, γ_{22}, and γ_{32} (the effects of the family member's mental health on the older person's trajectory). This cross-care partner effect is similar to the interpersonal cross-spouse effect described by Davey et al. (2001) as capturing a truly interpersonal or dyadic characteristic. Such cross-care partner effects allow for a more comprehensive examination of dyadic processes and are often overlooked in dyad research (Davey et al.).

The variables type of family dyad and family member's mental health were entered into the Level 2 model simultaneously to examine their association with the variation in family member's and older person's trajectories of mutuality. Inspection of Columns 5 through 8 in Table 2 indicates that type of family dyad was significantly associated with family member's mutuality at baseline ($\gamma_{41} = 0.43$, $p < .01$). On average, family members married to the older person had significantly higher levels of mutuality at baseline than family members caring for a parent, controlling for average family member's mental health. There was no significant effect of type of family dyad on older person's baseline mutuality. These effects are displayed in Figure 2.

Family member's mental health was not only significantly associated with family member's mutuality at baseline ($\gamma_{42} = 0.01$, $p < .01$) but also showed a significant cross-partner effect with older person's mutuality at baseline ($\gamma_{12} = 0.01$, $p < .01$). As higher scores indicate better mental health, on average, the better the family member's mental health, the higher their own mutuality and that of the older person for whom they are caring.

Random effects. Columns 7 through 12 in Table 3 contain the variance components for the conditional model. It is possible to calculate the percent of variance in each growth parameter that is explained by the conditional model by subtracting the residual variance component in the conditional model from the residual variance component in the unconditional model and then converting to a percentage. For instance, the model explains 25% of the variance in family member's mutuality at baseline ([0.48 − 0.36]/0.48 = 0.25). Overall, the two predictors do a better job of explaining variance in the family member's trajectory as compared to the older person's trajectory, accounting for 25% of the variance in family member's mutuality at baseline and 10% of the variance in the family member's linear slope. Variance in the quadratic slope remained unchanged for both family members and older persons.

Extensions of the Model

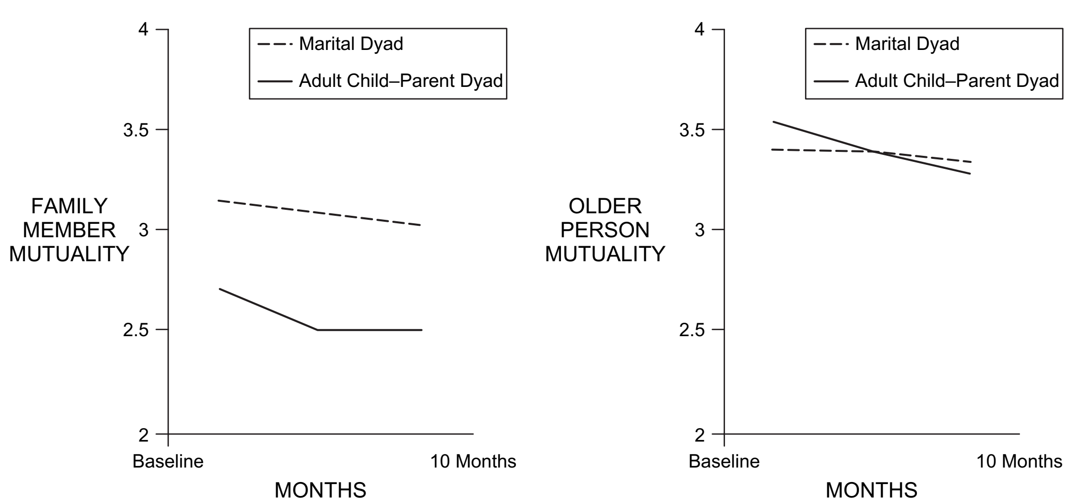
The multivariate outcomes dyad models presented in this paper can be extended to the case of the triad or family under the assumption that (a) family members have distinguishable roles and (b) outcome data gathered from each member are relational in nature (all individuals are responding to the same scale or survey items). It is likely that problems with data sparseness will arise when extending the model to families where the number of members varies across families, that is, there will be very few large families. In multilevel modeling, this is a question of the robustness of the model to large amounts of missing data. One strategy, conditional on the research questions that the researcher wants to investigate, would be to sample selected family members so as to ensure that the same number is included for each family.

These models can also be extended to examine truly contextual effects, for example, care dyads nested within different communities, clinics, or health care providers using a three-level model. Finally, similar to the work by Barnett et al. (1995) and Raudenbush et al. (1995), such models can also include time-varying covariates that capture the association between changes in mental health and changes in mutuality over time.

Implications for Family Research

The models illustrated in this paper demonstrate the advantages of multilevel modeling over traditional dyad analyses in several ways. First, the models examined the relational character of change within dyads by comparing average trajectories for both members while controlling for the interdependency of the outcome scores. Older persons had a significantly higher level of mutuality over time, and family members

FIGURE 2. THE EFFECTS OF TYPE OF DYAD RELATIONSHIP (MARITAL DYAD VS. ADULT CHILD–PARENT DYAD) ON AVERAGE MUTUALITY TRAJECTORIES FOR FAMILY MEMBERS AND OLDER PERSONS, CONTROLLING FOR BASELINE FAMILY MEMBER'S MENTAL HEALTH ($N = 74$ DYADS). HIGHER SCORES INDICATE GREATER MUTUALITY WITH A POSSIBLE RANGE OF 0–4 AND BETTER MENTAL HEALTH WITH A POSSIBLE RANGE OF 0–100.



showed a significant linear trend. Second, the models allowed for differential patterns of prediction across members of the dyad. We found the type of relationship (marital vs. parent-child) to be a significant predictor for family member's mutuality but not older person's mutuality. Using more complex models to explore differential patterns of prediction can provide insight into important dyadic processes. Third, the model estimated the cross-care partner effects of mental health. The mental health of the family member at baseline was not only significantly associated with how the family member perceived the care relationship but also influenced the older person's perception of the care relationship. Such cross-partner effects allow us to understand the interactive and dynamic nature of the dyad relationship over time and its effects on both members' well-being.

In the past decade, multilevel modeling has greatly enhanced family researchers' ability to examine the contextual effects of communities on individual development. The ability to model such nested data has advanced both family science and clinical work. We suggest that the wider adoption of multilevel modeling to examine the context of both dyad and family will advance family research in other ways. First, multilevel modeling will make it possible to model within-dyad (and within-family) variation and pose new questions about within-family relationships. Researchers can begin to examine the dynamics of the family context over time and the differentiating effects of individual roles within the same family. For example, much family care research has been limited to comparing the experiences of spouses and adult children from separate families (e.g., Clyburn, Stones, Hadjistavropoulos, & Tuokko, 2000; Lawrence, Tennstedt, & Assmann, 1998; Semple, 1992; Yates, Tennstedt, & Chang, 1999). The ability to compare the family experiences and health outcomes of spouses and adult children within the same family unit, however, will shed important light on these distinct family roles in the context of severe illness.

Second, multilevel modeling will change the way we evaluate both individual and family interventions (Lyons & Sayer, 2005). Multilevel modeling allows us to evaluate the effects of both individual- and family-targeted interventions for a more complete understanding of their costs and benefits at both levels. By examining the effects of an intervention on a dyad or family, we can begin to see not only whether the intervention is successful for the target individual but also for other family members. It is possible that individually targeted interventions may have benefits for all members, be detrimental for all or none, or have little or no effect for all or none. We can also investigate whether the intervention has any effect on a family as a whole, such as decreasing the discrepancy among members.

Those readers interested in further discussion of the role of multilevel modeling in evaluating the differential effects of interventions on dyads and individuals are referred to Lyons and Sayer (2005). Multilevel dyad models parameterized to directly predict variation around dyad discrepancy are described by Lyons et al. (2002) and Sayer and Klute (2005).

Conclusion

Until recently, researchers have had few statistical tools to examine how individuals interact in dyadic and family relationships and how such families are affected by life transitions such as a severe illness of one member. Such questions are multilevel in nature, involving more than one unit of analysis, and methods that fail to address the hierarchical nature of families consequently fail to illuminate variation both within and between family processes. For research that is truly interested in the dyad or family unit as a context, and the nature of the processes and interactions that make up that context, multilevel modeling is an appropriate and powerful methodology. We hope the examples presented in this paper begin to demonstrate the potential of multilevel modeling to advance the fields of family and marital research.

Note

We gratefully acknowledge Barbara Stewart and Patricia Archbold for their helpful comments on this manuscript. Support to the first author was provided by Grant R03 AG022110-01 from the National Institute on Aging. Illustrative data were collected with funding from Grant R01 AG17909-04 from the National Institute on Aging, National Institute of Nursing Research, and Agency for Healthcare Policy and Research.

References

Aneshensel, C. S., Pearlin, L., Mullan, J. T., Zarit, S. H., & Whitlatch, C. J. (1995). *Profiles in* *caregiving: The unexpected career*. San Diego: Academic Press.

Archbold, P. G., Stewart, B. J., Greenlick, M. R., & Harvath, T. (1990). Mutuality and preparedness as predictors of caregiver role strain. *Research in Nursing & Health*, *13*, 375–384.

Barnett, R. C., Marshall, N. L., Raudenbush, S. W., & Brennan, R. T. (1993). Gender and the relationship between job experiences and psychological distress: A study of dual-earner couples. *Journal of Personality & Social Psychology*, *64*, 794–806.

Barnett, R. C., Raudenbush, S. W., Brennan, R. T., Pleck, J. H., & Marshall, N. L. (1995). Change in job and marital experiences and change in psychological distress: A longitudinal study of dual-earner couples. *Journal of Personality & Social Psychology*, *69*, 839–850.

Biesanz, J. C., Deeb-Sossa, N., Papadakis, A. A., Bollen, K. A., & Curran, P. J. (2004). The role of coding time in estimating and interpreting growth curve models. *Psychological Methods*, *9*, 30–52.

Bost, K. K., Cox, M. J., & Payne, C. (2002). Structural and supportive changes in couples' family and friendship networks across the transition to parenthood. *Journal of Marriage and Family*, *64*, 517–531.

Carter, J. H., & Nutt, J. G. (1998). Family caregiving: A neglected and hidden part of health care delivery [Editorial]. *Neurology*, *51*, 1245–1246.

Carter, J. H., Stewart, B. J., Archbold, P. G., Inoue, I., Jaglin, J., Lannon, M., Rost-Ruffner, E., Tennis, M., McDermott, M. P., Anyot, D., Barter, R., Cornelius, L., Demong, C., Dobson, J., Duff, J., Erickson, J., Gardiner, N., Gauger, L., Gray, P., Kanigan, B., Kiryluk, B., Lewis, P., Mistura, K., Malapira, T., Pay, M., Sheldon, C., Winfield, L., Wolfington-Shallow, K., Zoog, K., & The Parkinson Study Group. (1998). Living with a person who has Parkinson's disease: The spouse's perspective by stage of disease. Movement Disorders, 13, 20–28.

Clyburn, L. D., Stones, M. J., Hadjistavropoulos, T., & Tuokko, H. (2000). Predicting caregiver burden and depression in Alzheimer's disease. *Journals of Gerontology Series B—Psychological Sciences & Social Sciences*, *55B*, S2–S13.

Davey, A., Fincham, F. D., Beach, S. R. H., & Brody, G. H. (2001). Attributions in marriage: Examining the entailment model in dyadic context. *Journal of Family Psychology*, *15*, 721–734.

Davey, A., & Szinovacz, M. E. (2004). Dimensions of marital quality and retirement. *Journal of Family Issues*, *25*, 431–464.

Gonzalez, R., & Griffin, D. (1997). On the statistics of interdependence: Treating dyadic data with respect. In S. Duck (Ed.), *Handbook of personal relationships* (2nd ed., pp. 271–302). Chichester, U.K.: Wiley & Sons.

Hoffmann, J. P. (2002). The community context of family structure and adolescent drug use. *Journal of Marriage and Family*, *64*, 314–330.

Hussey, D. L., & Guo, S. (2003). Measuring behavior change in young children receiving intensive school-based mental health services. *Journal of Community Psychology*, *31*, 629–639.

Kane, R. L., & Kane, R. A. (Eds.). (2000). *Assessing older persons: Measures, meaning, and practical applications*. New York: Oxford University Press.

Kenny, D. A. (1996). Models of non-independence in dyadic research. *Journal of Social and Personal Relationships*, *13*, 279–294.

Klute, M. M., Crouter, A. C., Sayer, A. G., & McHale, S. M. (2002). Occupational self-direction, values, and egalitarian relationships: A study of dual-earner couples. *Journal of Marriage and Family*, *64*, 139–151.

Kurdek, L. A. (2003). Methodological issues in growth-curve analyses with married couples. *Personal Relationships*, *10*, 235–266.

Lawrence, R. H., Tennstedt, S. L., & Assmann, S. F. (1998). Quality of the caregiver-care recipient relationship: Does it offset negative consequences of caregiving for family caregivers? *Psychology & Aging*, *13*, 150–158.

Lyons, K. S., & Sayer, A. G. (2005). Using multilevel modeling in caregiving research. *Aging & Mental Health*, *9*, 189–195.

Lyons, K. S., Stewart, B. J., Archbold, P. G., Carter, J. H., & Perrin, N. (2004). Pessimism and optimism as early-warning signs for compromised health in Parkinson's disease caregiving. *Nursing Research*, *53*, 354–362.

Lyons, K. S., Zarit, S. H., Sayer, A. G., & Whitlatch, C. J. (2002). Caregiving as a dyadic process: Perspectives from caregiver and receiver. *Journals of Gerontology: Psychological Sciences*, *57B*, P195–P204.

Raudenbush, S. W., Brennan, R. T., & Barnett, R. C. (1995). A multivariate hierarchical model for studying psychological change within married couples. *Journal of Family Psychology*, *9*, 161–174.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models* (2nd ed.). Newbury Park, CA: Sage.

Raudenbush, S. W., Bryk, A. S., & Congdon, R. (2004). *Hierarchical linear and nonlinear modeling*. Lincolnwood, IL: SSI.

Rayens, M. K., & Svavarsdottir, E. K. (2003). A new methodological approach in nursing research: An actor, partner, and interaction effect model for family outcomes. *Research in Nursing & Health*, *26*, 409–419.

Sayer, A. G., & Klute, M. M. (2005). Multilevel models for dyads. In V. L. Bengtson, A. C. Acock, K. R. Allen, P. Dilworth-Anderson, & D. M. Klein (Eds.), *Sourcebook on family theory and research* (pp. 289–313). Thousand Oaks, CA: Sage.

Semple, S. J. (1992). Conflict in Alzheimer's caregiving families: Its dimensions and consequences. *Gerontologist*, *32*, 648–655.

Simons, R. L., Lin, K.-H., Gordon, L. C., Brody, G. H., Murry, V., & Conger, R. D. (2002). Community differences in the association between parenting practices and child conduct problems. *Journal of Marriage and Family*, *64*, 331–345.

Teachman, J. D., Carver, K., & Day, R. (1995). A model for the analysis of paired data. *Journal of Marriage and the Family*, *44*, 889–900.

Thompson, L., & Walker, A. J. (1982). The dyad as the unit of analysis: Conceptual and methodological issues. *Journal of Marriage and the Family*, *44*, 889–900.

Townsend, A. L., Miller, B., & Guo, S. (2001). Depressive symptomatology in middle-aged and older married couples: A dyadic analysis. *Journals of Gerontology: Social Sciences*, *56B*, S352–S364.

Ware, J. E., Jr., & Gandek, B. (1998). Overview of the SF-36 Health Survey and the International Quality of Life Assessment (IQOLA) project. *Journal of Clinical Epidemiology*, *51*, 903–912.

Yates, M. E., Tennstedt, S., & Chang, B.-H. (1999). Contributors to and mediators of psychological well-being for informal caregivers. *Journals of Gerontology: Psychological Sciences*, *54B*, P12–P22.