20 Multilevel Modeling Approaches to the Study of LGBT-Parent Families: Methods for Dyadic Data Analysis

JuliAnna Z. Smith, Aline G. Sayer, and Abbie E. Goldberg

One of the most central pursuits of family theory and research is to better understand and explore the dynamics of interpersonal family relationships. Understanding these relationships is furthered by collecting information on multiple family members (Jenkins et al., 2009). However, by their very nature, family members' experiences are interdependent, and this interdependence complicates the question of how to analyze data from multiple family members (Atkins, 2005; Bolger & Shrout, 2007; Jenkins et al., 2009; Sayer & Klute, 2005). Indeed, data interdependence precludes the use of many statistical methods that assume the errors are independent, such as ordinary least squares (OLS) regression or standard analysis of variance (ANOVA). Several statistical methods that take into account the dependency in family members' outcomes are available to researchers and have become the standard in family research journals. Many of the most commonly used approaches, however, require one to distinguish family members on the basis of some characteristic meaningful to the analyses (Sayer & Klute, 2005). For example, in parent/child dyads one can easily distinguish dyad members on the basis of whether they are the parent or child (Papp, Pendry, & Adam, 2009). In research on heterosexual couples, partners are most commonly distinguished on the basis of gender (Atkins, Klann, Marín, Lo, & Hahlweg, 2010; Claxton, O'Rourke, Smith, & DeLongis, 2012; Papp, Goeke-Morey, & Cummings, 2007; Perry-Jenkins, Smith, Goldberg, & Logan, 2011; Raudenbush, Brennan, & Barnett, 1995). Such approaches to distinguishing partners on the basis of gender, however, are clearly not useful to researchers of same-sex couples. In some cases same-sex partners may be distinguished on the basis of some other characteristic, such as biological versus nonbiological parent (Goldberg & Perry-Jenkins, 2007; Goldberg & Sayer, 2006), where that distinction is relevant to the analyses. In other cases, however, no such meaningful distinctions can be made—for example, in many analyses of lesbian/gay nonparent couples or lesbian/gay adoptive parents, wherein neither partner is the biological parent. In these instances, alternate statistical methods must be employed.

This chapter discusses the challenges faced by researchers analyzing data from multiple family members. It focuses on couples, as well as

J.Z. Smith, M.A. (✉)
Department of Psychology, Center for Research on Families, University of Massachusetts, 135 Hicks Way, 622 Tobin Hall, Amherst, MA 01003, USA
e-mail: juliannzsmith@mac.com; julianns@acad.umass.edu

A.G. Sayer, Ph.D.
Department of Psychology, Center for Research on Families, University of Massachusetts, 616 Tobin Hall, 135 Hicks Way, Amherst, MA 01003, USA
e-mail: sayer@psych.umass.edu

A.E. Goldberg, Ph.D.
Department of Psychology, Clark University, 950 Main Street, Worcester, MA 01610, USA
e-mail: agoldberg@clarku.edu

A.E. Goldberg and K.R. Allen (eds.), *LGBT-Parent Families: Innovations in Research and Implications for Practice*, DOI 10.1007/978-1-4614-4556-2_20, © Springer Science+Business Media New York 2013

advances in research methods using multilevel modeling (MLM). MLM, which is a fairly straightforward extension of the more familiar OLS multiple regression, provides one of the more versatile and accessible approaches available to model couple and family data (Sayer & Klute, 2005). We begin by discussing the role of multilevel modeling in family research, in general, and in analyzing dyadic (or paired) data, more specifically. Next, we consider some of the common difficulties encountered by LGBT researchers examining family data. We then describe the basic multilevel models available to researchers analyzing (a) cross-sectional and (b) longitudinal dyadic data. Next, we address the application of these models to analyses of multiple informant data, when multiple family members provide reports of the same outcome. In addition, we present some considerations that researchers using these statistical methods should take into account.

Multilevel Modeling in Family Research

The use of MLM has become common in family journals (e.g., Brincks, Feaster, & Mitrani, 2010; Kretschmer & Pike, 2010; Soliz, Thorson, & Rittenour, 2009), particularly in research on heterosexual couples (e.g., Atkins et al., 2010; Papp et al., 2007; Perry-Jenkins et al., 2011). Notably, its adoption by researchers who study LGBT couples and families has been somewhat slower. In part, this is because the area of LGBT couples and families is relatively new, and much of the research has been qualitative and exploratory as opposed to quantitative (see Goldberg, 2010, for a review). In addition, studies that do use quantitative methods often rely on fairly small sample sizes of LGBT couples and families (e.g., Goldberg & Sayer, 2006; Patterson, Sutfin, & Fulcher, 2004), thereby decreasing power and the ability to detect effects. Small sample sizes may lead researchers to use other methods in preference to maximum likelihood methods such as multilevel modeling which perform best with large samples (Raudenbush, 2008). Finally, there are often additional complications when analyzing same-sex couples whose members are not clearly distinguishable from one another on the basis of some central characteristic such as gender. Such couples or dyads are termed "indistinguishable" or "exchangeable" and require methods designed to take this indistinguishability into account. Treating dyad members as indistinguishable requires the use of MLM approaches that may be less familiar to many family researchers.

Several excellent recent papers address the use of structural equation modeling (SEM) strategies to analyze data from indistinguishable dyads (Olsen & Kenny, 2006; Woody & Sadler, 2005). For applied family researchers, however, multilevel modeling provides a more straightforward way to analyze data collected on multiple family members. A fairly large and growing body of work discusses the application of MLM to heterosexual couples using models for distinguishable dyads (Bolger & Shrout, 2007; Raudenbush et al., 1995; Sayer & Klute, 2005). Much less is available on its application to indistinguishable couples (Kenny, Kashy, & Cook, 2006). In particular, there is a need to bring together recent advances in several areas: (a) the analyses of indistinguishable dyads, (b) advances in longitudinal analyses (Kashy, Donnellan, Burt, & McGue, 2008), and (c) the analyses of mixed samples, such as analyses including lesbian, gay male, and heterosexual couples (West, Popp, & Kenny, 2008). Consequently, this chapter focuses on multilevel modeling approaches to analyzing dyadic data when couple members can be considered indistinguishable. While these approaches are valuable for the study of same-sex couples, they are also useful in the study of twins, friends, roommates, and other types of relationships where members cannot be distinguished from each other on some meaningful characteristic (Kenny et al., 2006). For this reason, the information presented in this chapter may be useful and relevant to family scholars more generally.

Family theorists from a wide range of perspectives including family systems theory, life course theory, social exchange theory, symbolic interaction theory, conflict theory, and social ecological

theory have long been interested in the relationships between family members and how those relationships affect family members. For example, family systems theory views individuals as part, not only of a family, but also of multiple, mutually influencing family subsystems (Cox & Paley, 1997). Individuals' experiences and their dyadic relationships with other family members affect not only those directly involved but other individuals and relationships within the family system as well. Life course theory examines changes in the intertwined lives of family members over the life span (Bengtson & Allen, 1993). Finally, ecological theory posits the importance of understanding the family as a central social context that influences all of the individuals within it (Bronfenbrenner, 1988). Research examining data from multiple family members allows researchers to start to tease apart these complex family relationships. For example, Georgiades, Boyle, Jenkins, Sanford, and Lipman (2008) examined multiple family members' reports of family functioning ($N = 26{,}614$ individuals in 11,023 families). Using MLM enabled them to distinguish shared perceptions of family functioning from unique individual perceptions.

In addition, collecting information from more than one individual per family allows for the examination of the association between family members' scores (Bolger & Shrout, 2007). Multilevel modeling provides a means of better understanding the relationship between separate reports of the same outcomes, while accounting for the correlation between family members' outcomes. In addition, it provides a means of disentangling the variability in the outcome. The variance in the outcome is due to two sources: within-family variability and between-family variability. MLM methods provide a means for separating the variability in the outcome into these two sources, as well as appropriately testing both family-level and individual-level predictors of that variability. It is not surprising, therefore, that MLM has become widely used in family research. The nature of family research has subsequently led to adaptations of MLM approaches to suit the specialized needs of this field, most notably in the area of modeling couple data (or dyadic data more generally; e.g., Barnett, Marshall, Raudenbush, & Brennan, 1993; Raudenbush et al., 1995).

Key Issues in Analyzing Data from LGBT Couples and Families

The Issue of Dependence

It is important to clarify why special statistical methods may be required when analyzing data from multiple family members. An assumption underlying conventional statistical methods such as OLS regression and standard ANOVAs is that the residuals (errors) are independent. This assumption is untenable in the case of dyadic or family data. Partners who are in a relationship are likely to have outcomes that are similar, and this similarity or dependency must be taken into account when performing statistical analyses. Failure to take into account dependence in the outcome scores results in inaccurate estimates of the standard errors, leading to both Type I and Type II errors (Griffin & Gonzalez, 1995; Kenny & Judd, 1986; Kashy & Kenny, 2000; Kenny et al., 2006). In addition, failure to account for dependency in the outcome can also lead to incorrect estimates of effect sizes (West et al., 2008).

There are a number of reasons why family members' outcomes may be associated (Kenny et al., 2006). For example, partners may have chosen each other at least partly on the basis of shared interests in community involvement (mate selection). Alternately, a small family income may affect the financial confidence of all of the members of a particular family (shared context). Similarly, family members who live together are likely to be affected by each other's moods (mutual influence). Statistical methods such as paired sample *t*-tests and repeated measures ANOVA do adjust the estimates for the dependency in the outcome and can be used to answer many basic research questions. For example, a researcher may investigate if lesbian mothers and their teen daughters have mean differences in the level of conflict they report in their relationship. Addressing more complex questions requires the application of

methods that allow for the estimation of both the average effect for the entire group and the variability of each dyad around the dyad average. In addition, MLM enables the examination of the effects of both individual- (e.g., age or stress level) and family-level (e.g., number of children or family income) variables (Kenny et al., 2006; Sayer & Klute, 2005). In other words, instead of treating the dependence between family members' reports as a nuisance to be adjusted for, MLM enables researchers to treat this dependence as interesting in its own right and to explore predictors of it.

The Issue of Distinguishability

When studying same-sex couples, researchers are often faced with an additional methodological difficulty. For example, most analyses of heterosexual couples within family studies distinguish between the two members of the couple on the basis of gender (Atkins et al., 2010; Claxton et al., 2012; Papp et al., 2007; Perry-Jenkins et al., 2011; Raudenbush et al., 1995). In research on same-sex couples, distinguishing partners by gender is obviously not an option. In some instances same-sex partners should be distinguished on the basis of some other characteristic, as that distinction is important for the analyses conducted. For example, in Abbie Goldberg's work on lesbian couples who used alternative insemination to become parents ($N = 29$–34 couples), she distinguished between the biological mothers and the nonbiological mothers and found differential predictors of relationship quality and mental health across the transition to parenthood (Goldberg & Sayer, 2006; Goldberg & Smith, 2008a). Other distinguishing features that may be relevant to analyses might be work status (e.g., working/not working, in single-earner couples), primary/secondary child caregiver status, or diseased/not diseased (O'Rourke et al., 2010).

It is important that the distinction between dyad members is justified by the research questions being asked and the analyses being conducted and is thereby meaningful in a substantive sense. As it is always possible to find some a distinguishing feature, however arbitrary, it is important to carefully evaluate whether the distinguishing feature is in fact relevant. There are, for example, times when distinguishing heterosexual couples based on gender may not be relevant to the analyses being conducted (Atkins, 2005; Kenny et al., 2006). The use of a particular distinguishing feature should be supported by the theoretical frameworks guiding the research, prior research findings suggesting that this is a meaningful distinction for the analyses being conducted, and by empirical investigation of the data being examined (Kenny et al., 2006). Kenny and Ledermann (2010) contend that distinguishability must be supported empirically. In other words, if dyad members are to be treated as distinguishable in the analyses, additional analyses should be conducted to give empirical support for this decision. Kenny et al. (2006) suggest that an Omnibus Test of Distinguishability be conducted using structural equation modeling, to examine the covariances between all variables in a model, for every model presented in the analyses, in order to show that the data support distinguishing dyad members.

There are also methods that can be used within the context of multilevel modeling to empirically support the use of a particular feature to distinguish between dyad members. Consider, for example, the analyses of mental health in lesbian inseminating couples, where partners were distinguished by whether or not they were the biological mother of the child (Goldberg & Smith, 2008a). The MLM approach for distinguishable dyads provides separate parameter estimates for the two partners based on the distinguishing feature (in our example, biological mother or nonbiological mother). Researchers can test whether these estimates are statistically significantly different from each other, by fitting a second model, in which these two separate parameter estimates are constrained to be equal. Model comparison tests are then used to determine which model is a better fit to the data. If there is no significant decrement in model fit, then there is not enough of a difference in the partners' estimates to justify the estimation of two separate parameters. If there is a significant decrement, this supports the decision to treat partners as being meaningfully

distinguished on the basis of the selected distinguishing feature (i.e., in this case, biological versus nonbiological mother).

It is possible that researchers will find that only some parameter estimates differ. Those parameters that are not found to be significantly different can then be constrained to be equal, creating a more parsimonious model. Such an approach was used in Goldberg and Smith's (2008a) examination of changes in the anxiety of lesbian inseminating couples over time ($N = 34$ couples). Their analyses revealed that while the effect of some factors such as neuroticism did not significantly differ for biological and nonbiological lesbian mothers, other factors did have a differential effect on biological and nonbiological mothers. For example, work hours and proportional contribution to housework were related to higher levels of anxiety only for biological mothers, while high infant distress and low instrumental social support were related to greater increases in anxiety only in nonbiological mothers. Such differential findings strongly supported the decision to distinguish partners on the basis of whether or not they were the biological mother.

MLM Approaches to Analyzing Data from Indistinguishable Dyads

In many cases in LGBT couple research, a salient, distinguishing feature will not be available for researchers. Having a distinguishing feature simplifies analyses as it allows the researcher to assign each member to a group based on that distinction and then examine these separate groups in the analyses. As a result, some researchers may be tempted to deal with the lack of a distinguishing feature on which to assign dyad members to groups by randomly assigning members to one of two groups (e.g., partner A and partner B) and then treating them as if they were distinguishable or by using an arbitrary characteristic to distinguish them (see Kenny et al., 2006). The problem with such an approach is that it can lead to erroneous findings. The assignment to a group is purely arbitrary and, yet, findings will differ depending on how the individuals are assigned. For example, when examining couple data, one of the first questions a researcher may want to consider is "How correlated are partners' scores?" Once the researcher has distinguished between the two partners and assigned them to separate groups, the researcher can simply examine the correlation between the two partners' scores. Unfortunately, however, the estimate of this correlation will differ depending on the way in which partners were assigned to groups (see Kenny et al., 2006, for a more detailed discussion of this issue).

It is important to arrive at an accurate estimate of this correlation between partners' scores. This estimate is the interclass correlation coefficient (ICC), and it provides crucial information about the extent to which family members' scores are associated (and, thereby, the degree of dependence in their reports). As mentioned above, in the case of distinguishable dyads, the correlation between partners' scores can be easily assessed using a Pearson's product moment correlation. While it is more difficult to obtain an accurate estimate of the ICC in the case of indistinguishable dyads, there are two basic methods. Kenny et al. (2006) describe how ANOVA can be used to correctly estimate this correlation, but the ICC is more commonly and more easily estimated using multilevel modeling.

Cross-Sectional Model for Indistinguishable Dyads

Multilevel modeling provides a relatively simple extension of OLS regression, which takes into account the nesting of data within families or couples. In this statistical approach, the variance in the outcome is partitioned into the variance that occurs *within* couples (how partners differ from each other) and the variance that occurs *between* couples (how couples differ from each other). Predictors, both those that vary by couples (such as number of children and length of relationship) and those that vary by partner (such as age or mental health status), can then be added to explain this variance. In the model for the cross-sectional analysis of dyadic data, the

	FAMID	MEMBER	FAMSUP	A1AGE	P1AGE	A1EDUC	P1EDUC	A1PINC	P1PINC
1	1	1	3.10	43	43	5	5	$9.50	2.10
2	1	2	1.45	43	43	5	5	$2.10	9.50
3	2	1	3.50	40	53	5	6	$9.00	14.00
4	2	2	1.95	53	40	6	5	$14.00	9.00
5	3	1	2.85	36	37	5	6	$4.50	9.50
6	3	2	3.50	37	36	6	5	$9.50	4.50
7	4	1	1.85	38	41	4	2	$6.60	3.85
8	4	2	3.55	41	38	2	4	$3.85	6.60

Fig. 20.1 Example of a Level-1 (within couples) data file for the analysis of cross-sectional dyadic data

multilevel model generally used to examine individuals who are nested within groups (such as students within classrooms, workers within organizations, or patients within hospitals) is adapted in very specific ways to deal with the small number of cases or individuals in each dyad. For example, one common area of adaptation is in the specification of the error structure (i.e., using compound symmetry), which is the way in which the dependence of the outcome scores is modeled.

The MLM approach to indistinguishable dyads is actually a simpler model than the one most commonly used for distinguishable dyads (Kenny et al., 2006). Several studies of same-sex couples have used this approach (e.g., Goldberg & Smith, 2008b, 2009b; Kurdek, 1998). For example, Lawrence Kurdek (2003) used this approach to analyze differences between gay and lesbian cohabiting partners' relationship beliefs, conflict resolution strategies, and level of perceived social support variables in a sample of 80 gay male and 53 lesbian couples.

The most basic model is an unconditional model, with no predictors at either level; this is often referred to as a random intercept model (Raudenbush & Bryk, 2002). This model provides estimates for the grand mean of the outcome across all couples as well as estimates for the two sources of variability: within couples and between couples. We calculate the ICC from these two estimates of variability. The ICC provides two central pieces of information: (a) the extent of the dependence within couples on the outcome and (b) the proportion of variance that lies *between* couples versus the proportion that lies *within* couples. Any ICC larger than a few percentage points indicates a degree of dependence in the data that cannot be overlooked and justifies the use of MLM.

It is easiest to understand multilevel models if one looks at the levels separately. In the cross-sectional model for dyads, Level 1 provides the *within*-couple model, in which individual responses are nested within couples, while Level 2 provides the *between*-couples model. (Examining the structure of the data for the two levels, as required by the software program HLM, can help one better understand the distinction between these levels; see Figs. 20.1 and 20.2; Raudenbush, Bryk, & Congdon, 2004.) In (20.1) of the unconditional model, the intercept, β_{0j}, represents the average outcome score for each couple, and r_{ij} represents the deviation of each member of the couple from the couple average. This intercept is treated as randomly varying; that is, it is allowed to take on different values for each couple. The intercepts that are estimated for each couple are treated as an outcome variable at Level 2. The intercept in the Level-2 equation, (20.2), γ_{00}, provides an estimate of the average outcome score across couples and u_{0j} represents the deviation of each couple from the overall average across all couples.

Level 1 (*within* couples):

$$Y_{ij} = \beta_{0j} + r_{ij}, \tag{20.1}$$

Level 2 (*between* couples):

$$\beta_{0j} = \gamma_{00} + u_{0j}, \tag{20.2}$$

	FAMILYID	lesbian	PrivAdop	PubAdopt	IntAdopt
1	1	1	1	0	0
2	2	1	1	0	0
3	3	1	0	0	1
4	4	1	1	0	0
5	5	1	1	0	0
6	6	1	0	1	0
7	7	1	0	0	1
8	8	1	1	0	0

Fig. 20.2 Example of a Level-2 (between couples) data file for the analysis of cross-sectional dyadic data

where Y_{ij} represents the outcome score of partner i in dyad j, where $i = 1, 2$ for the two members of the dyad. In addition to the above "fixed effect" estimates (e.g., the γ_{00}'s), estimates of the variance of the "random effects" both within and between couples are provided (e.g., the variance of the r_{ij}'s and the u_{0j}'s), as well as the covariance between partners. Predictors can then be added to the model, with those that vary within couples (e.g., partners' ages) added at Level 1:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{Age})_{ij} + r_{ij}, \qquad (20.3)$$

and those that vary between couples (e.g., duration of time in a relationship together) added at Level 2:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{Duration}) + u_{0j}. \qquad (20.4)$$

We can add a variable at Level 2 that provides us with a way to tease out important group differences in the couple averages, such as the type of couple. For example, in Abbie Goldberg's research on lesbian, gay male, and heterosexual adoptive couples, this multilevel modeling approach is used to provide estimates of means for each group (on reports of love, conflict, and ambivalence), as well as to test for differences in these means (Goldberg, Smith, & Kashy, 2010). To examine group means, a dichotomous variable is created that indicates the type of couple (e.g., gay male or heterosexual), which is then entered at Level 2. The intercept provides the mean level of the outcome for the reference group (lesbian, in this case), while the coefficient for the predictor (e.g., gay male) indicates the difference between that group and the reference group.

Considering Partner Effects

Personal relationship theory, which examines the predictors, processes, and outcomes of close relationships, has shown the importance of considering the role of partner characteristics in dyadic research (Kenny & Cook, 1999). It may not be immediately evident how such a model can be used to examine partner effects—that is, the association between one partner's predictor with the other partner's outcome score. It is helpful to think of these associations within the context of the Actor–Partner Interdependence Model (APIM; Campbell & Kashy, 2002; Cook & Kenny, 2005). Using this approach, one simultaneously considers the respondent's value on a predictor such as age as well as the respondent's partner's value in

relationship to the outcome. For example, Fergus, Lewis, Darbes, and Kral (2009) found that in examining the HIV risk of gay men ($N=59$ couples), it was important to consider not only individuals' own integration into the gay community but also their partners' integration. In the MLM approach, both of these predictors are entered into the model at Level 1 (Kenny et al., 2006).

Level 1 (within couples):

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{ActorRace})_{ij} + \beta_{2j}(\text{PartnerRace})\, ij + r_{ij}, \quad (20.5)$$

Level 2 (between couples):

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + u_{0j} \\ \beta_{1j} &= \gamma_{10} + u_{1j} \\ \beta_{2j} &= \gamma_{20} + u_{2j}. \end{aligned} \quad (20.6)$$

The APIM model goes further, however, suggesting that it is necessary not only to consider both actor and partner characteristics as main effects but also to consider the interaction between them. This models the specific pairing of the two individuals in the couple. For example, the effect of parents' disciplinary style on the child's behavior may vary as a function of their partners' disciplinary style. In such a case, it would be important to test an interaction between actors' disciplinary style and partners' disciplinary style. Whenever the theoretical framework guiding the analyses and past research suggest the potential importance of such an interaction, and sample size permits its inclusion, it is crucial that the interaction term be included (Cook & Kenny, 2005).

Recent work in personal relationship theory has extended the APIM approach to specifically address the role of gender and sexual orientation (particularly in the area of partner preferences; West et al., 2008). West et al. (2008) argue for the need to include lesbian and gay male couples in research on the effects of partner gender. In addition, they contend that both actor gender and partner gender should be considered in analyses that examine data from both heterosexual (distinguishable) and same-sex (indistinguishable) couples. While they applaud the increasing work that includes all three of the above types of couples (e.g., Bailey, Kim, Hills, & Linsenmeier, 1997; Kurdek, 1997; Kurdek & Schmitt, 1986a, 1986b; Regan, Medina, & Joshi, 2001), they express regret that the analyses performed are too often limited to looking at differences among the three groups and do not include analyses that consider the effect of partner gender in conjunction with the actor's gender. They propose what they term a "factorial method" that considers respondent gender, partner gender, and "dyad gender" (i.e., the difference between same-gendered and different-gendered respondents, where dyad gender is the interaction between actor and partner gender). Examining group differences between lesbian, gay, and heterosexual couples without taking into account the gender differences within heterosexual couples may lead to an inadequate understanding of the data, as it conflates the scores for men and women within heterosexual couples. West and colleagues provide an example in which findings from a group difference approach (i.e., looking only at differences between lesbian, gay male, and heterosexual couples) showed that lesbian and gay male couples placed less importance on the social value of a partner (e.g., appeal to friends, similar social class background, financial worth) than heterosexual couples ($N=784$ lesbian, 969 gay male, and 4,292 heterosexual couples). When within-dyad gender differences are taken into account, however, the results showed that it was not that lesbians and gay men placed less emphasis on the social value of a partner than heterosexuals, but that heterosexual *women* placed much more emphasis on the social value of a partner than gay men and heterosexual men, with lesbians placing slightly more emphasis on social value than gay men.

Examining Change Over Time in Indistinguishable Dyads

To get a better grasp of longitudinal multilevel models for dyadic data, it is useful to understand how change is modeled in a basic (non-dyadic) multilevel model. The cross-sectional approach to

dyads addressed individuals nested within dyads, modeling individuals at Level 1 and couples at Level 2. When examining change over time, we are looking at multiple time points nested within each individual. Level 1 models change within individuals, while Level 2 models differences in change between individuals. There are essentially two MLM approaches to modeling change over time within dyads: (a) a 2-level model in which trajectories of change for both dyad members are modeled at Level 1, while between-dyad differences in change are modeled at Level 2 (Raudenbush et al., 1995), and (b) a 3-level model in which change over time within each individual is modeled at Level 1, individuals within dyads at Level 2, and between-dyad differences at Level 3 (Atkins, 2005; Christensen, Atkins, Yi, Baucom, & George, 2006; Kurdek, 1998, 2008; Simpson, Atkins, Gattis, & Christensen, 2008).

While conceptually, the 3-level approach might appear to make perfect sense, there is a statistical problem in terms of the random effects. That is, while it is a 3-level model in terms of the data structure, it is only a 2-level model in terms of the within-level variation. Consequently, most articles on dyadic multilevel modeling recommend the 2-level approach (Bolger & Shrout, 2007; Raudenbush et al., 1995; Sayer & Klute, 2005). Even proponents of the 3-level model admit to a reduction in power and related changes in findings when using this model in comparison to the 2-level model most commonly used for distinguishable dyads (Atkins, 2005). Recently, Deborah Kashy has developed an extension of the 2-level multilevel model generally used to examine change in distinguishable dyads, which can be applied in the case of indistinguishable dyads (Kashy et al., 2008). While Kashy's initial work was on twin research, more recent work has extended the use of this model to lesbian and gay male parents (Goldberg et al., 2010; Goldberg & Smith, 2009a, 2011). For example, in a study of lesbian, gay male, and heterosexual adoptive parents, this approach was used to examine preadoptive factors on relationship quality (love, conflict, and ambivalence) across the transition to adoptive parenthood (Goldberg et al., 2010; $N=44$ lesbian, 30 gay male, and 51 heterosexual couples). Parents who reported higher levels of depression, greater use of avoidant coping, lower levels of relationship maintenance behaviors, and less satisfaction with their adoption agencies before the adoption reported lower relationship quality at the time of the adoption. The effect of avoidant coping on relationship quality varied by gender. The use of a longitudinal model enabled them to examine change in relationship quality across this transition as well: Parents who reported higher levels of depression, greater use of confrontative coping, and higher levels of relationship maintenance behaviors prior to the adoption reported greater declines in relationship quality.

The longitudinal model for indistinguishable dyads is very similar to the distinguishable dyad model in which trajectories for both dyad members are modeled at Level 1, with separate intercepts and slopes modeled for each member of the dyad (Raudenbush et al., 1995). The two partners' intercepts are allowed to covary, as are their rates of change (slopes). Due to the inability to distinguish between dyad members, however, parameter estimates for the average intercept and average slope (the fixed effects) are pooled across partners as well as dyads (Kashy et al., 2008). In addition, drawing from approaches to modeling indistinguishable dyads in structural equation modeling (Olsen & Kenny, 2006; Woody & Sadler, 2005), this approach constrains the estimates of variance to be equal for partners. Similar to the distinguishable model, two (redundant) dummy variables, $P1$ and $P2$, are used to systematically differentiate between the two partners. In other words, if the outcome score is from partner 1, $P1=1$, and otherwise $P1=0$, and if the outcome score is from partner 2, $P2=1$, and otherwise $P2=0$. At Level 1 of the model (in which there are no predictors aside from Time), an intercept and slope for time for each partner is modeled:

Level 1 (within couples):

$$\begin{aligned} Y_{ijk} &= \beta_{01j}(P1) + \beta_{11j}(P1 \times \text{Time})_{1jk} \\ &\quad + \beta_{02j}(P2) + \beta_{12j}(P2 \times \text{Time})_{2jk} \\ &\quad + r_{ijk}, \end{aligned} \tag{20.7}$$

where Y_{ijk} represents the outcome score of partner i in dyad j at time k, and $i = 1, 2$ for the two members of the dyad.

In this model, intercepts and slopes can vary both within and between dyads. The inability to distinguish between dyad members would make it meaningless to have separate parameter estimates for member 1 and member 2; therefore the parameter estimates for the fixed effects are aggregated across dyad members. In the Level-1 equation (20.7), β_{01j} and β_{02j} represent the intercepts, for partner 1 and 2 in couple *j,* and estimate the level of depressive or anxious symptoms at the time of the adoption. Likewise, β_{11j} and β_{12j} represent the slopes for the two partners. These slopes estimate the change in the outcome over time. Unlike the distinguishable model, however, the intercepts and slopes are then pooled into only two Level-2 equations.

Level 2 (between couples):

$$\begin{aligned} \beta_{0ij} &= \gamma_{00} + u_{0ij} \\ \beta_{1ij} &= \gamma_{10} + u_{1ij}. \end{aligned} \tag{20.8}$$

As these two equations show, the intercepts are pooled not only between but also *within* dyads (i.e., across both i and j) to estimate the fixed effect, γ_{00}, which is the average intercept (or the average level of the outcome when Time = 0), and similarly, the slopes for time are pooled both between and within dyads to estimate the average slope, γ_{10} (or the average rate of change in the outcome across all partners).

The variance components are also pooled both between and *within* dyads. At Level 2, the variance in the intercept, $\mathrm{Var}(u_{0ij})$, represents the variability in the outcome at the time of the adoptive placement, and the variance in the slopes, $\mathrm{Var}(u_{1ij})$, represents the variability in how depressive or anxious symptoms change over time. The third variance component, $\mathrm{Var}(r_{ijk})$, is the variance of the Level-1 residuals (or the difference between the observed values of the outcome and the predicted values from the fitted trajectories). The variance of the Level-1 residuals is constrained to be equal for both partners and across all time points. In addition to the variances, several covariances commonly estimated in dyadic growth models are also included in this model. For example, the covariance between the two slopes estimating change for each person uniquely shows the degree of similarity in partners' patterns of change.[1]

Considerations When Modeling Change Over Time

When modeling change, the reliability of the change trajectories will be greatly improved with a greater number of assessment points (Raudenbush & Bryk, 2002; Willett, 1989). In addition, the use of more assessment points allows researchers to examine more complex patterns of change. For example, research on heterosexual-parent couples has shown relationship quality and many mental health outcomes such as depression to follow curvilinear trajectories particularly across the transition to parenthood (Perry-Jenkins, Goldberg, Pierce, & Sayer, 2007). Such patterns cannot be captured with only three time points.

While more time points are preferable, it is possible to fit the change models to examine change between two time points. Goldberg and Smith (2009a) used this approach to examine changes in perceived parenting skill in lesbian, gay male, and heterosexual adoptive couples after the adoption of their first child. Examination of change between only two time points is essentially a difference score. While not ideal, the use of multilevel modeling to generate difference scores provides better estimates of change than observed difference scores, as it provides a correction for

[1]In addition to the variances, Kashy et al.'s (2008) model for analyzing longitudinal data from indistinguishable dyads provides estimates for several covariances. Dyadic growth models often include three covariances. First, the covariance between the intercepts estimates the degree of similarity in partners' outcome scores when Time=0. Second, the covariance between the slopes estimates the degree of similarity in partners' patterns of change. Third, a time-specific covariance assesses the similarity in the two partners' outcome scores at each time point after controlling for all of the predictors in the model.

Two additional covariances are estimated using Kashy et al.'s (2008) approach. An intrapersonal covariance between the intercept and slope can be estimated to examine, for example, if having higher depressive symptoms at

measurement error. For an example in the distinguishable case, see Goldberg and Sayer's (2006) examination of change in relationship quality in 29 lesbian inseminating couples across the transition to parenthood.

Additional data preparation is necessary to estimate change between two time points. With only two time points at Level 1, there would be too few degrees of freedom to estimate two fixed effects (an intercept and rate of change) and the residual or error around the fitted regression line, unless additional information on the outcome was available and introduced into the modeling procedure. This additional information can be provided, however, by dividing the outcome measure into two parallel scales with comparable variance and reliability, allowing for the estimation of error (Raudenbush et al., 1995; Sayer & Klute, 2005).[2] In addition, the use of parallel scales provides a limited measurement component to the multilevel model and consequently a somewhat more accurate measure of both error and latent change scores. Future research, however, is needed to examine the reliability of the estimates for change from such models.

Multiple Informants

In family research, one often attains multiple reports of the same outcomes. For example, a researcher examining the behavior of children of lesbian mothers may have both mothers report on the child's behavior. While structural equation modeling provides the best available method of handling data from multiple reporters, multilevel modeling may also be used to examine these data. By using reports from both parents, researchers can introduce a limited measurement component to the model. While this is a new area for LGBT research, it is a growing area in family research. A particularly interesting study was conducted by Georgiades et al. (2008), who used MLM to examine reports of family functioning gathered from multiple family members ($N = 26{,}614$ individuals in 11,023 families). While using reports from multiple members of the family provided a better measure of family functioning, the use of MLM enabled the researchers to distinguish shared perceptions of family functioning from unique individual perceptions, as well as to examine predictors of these perceptions.

Dyadic models such as those presented in this paper can also be employed to examine reports from multiple informants. In the simplest application, MLM can provide a composite score across multiple reporters, as well as provide a measure of the degree of association between dyad members' reports. This approach was used by Meteyer and Perry-Jenkins (2010) to examine change in fathers' involvement in child care across the transition to parenthood in a sample of 98 heterosexual couples. The authors used a multilevel model with a single intercept and slope at Level 1 for each couple. This provided a composite estimate of the level of father involvement and the rate of change in involvement, based on both fathers' and mothers' reports of father involvement.

As an example, predictors of gay fathers' reports of their child's school involvement—an area that has received no scholarly attention—could be modeled using the indistinguishable models presented earlier in this chapter. In the dyadic, cross-sectional model, the composite

the time of adoption is related to greater increases in depressive symptoms over time. An interpersonal covariance between the intercept and slope can also be estimated to examine, for example, if partners of individuals with high initial stress experience greater increases in stress over time. As some software such as SPSS does not allow for estimation of these covariances, these are not always included in the models (Goldberg & Smith, 2009a, 2011; Goldberg et al., 2010). As these covariance estimates are less important, and less likely to affect findings, the use of models without them may well be adequate for most research. In fact, identical patterns of results have been found with and without the covariance constraints in the existing published literature (Goldberg & Smith, 2009a, 2011; Goldberg et al., 2010).

Note that the software program HLM does not allow for either variances or covariances to be constrained.

[2]Parallel scales are generally created based on the items variance. First, the variances of all of the items in the scale are determined. The items are then assigned to each of the two scales on the basis of their variance. In other words, the item with the most variance would be assigned to scale A. The item with the second highest variance would go in scale B. The item with the third highest variance would also go in scale B. The items with the next highest variance would go in scale A, as would the next, and so forth.

score for the dyad (dyad average) would be represented by the Level-1 intercept. MLM estimates the covariance between the fathers' scores, indicating the strength of the relationship between fathers' reports. Recall that in the MLM models, variance in the reports is partitioned into two sources: that which lies *between* dyads and that which lies *within* dyads. Researchers gain a better understanding of how much is within the dyads and hence between the two individuals who are reporting. Finally, couple-level predictors (e.g., relationship length, family income, number of children) of this composite could be entered at Level 2. Predictors of individual reports could be introduced at Level 1 (i.e., within couples).

With distinguishable dyads, the two-intercept model makes it easy to examine differential predictors of the two respondents' reports. For example, in the case of parent and child reports of child well-being, the model would include separate estimates for child reports and parent reports at Level 1. Predictors, such as family income, would be entered at Level 2. This model provides separate parameter estimates for the effect of income on parents' and children's reports. It is then possible to test whether these estimates are statistically different by constraining the two estimates to be the same and conducting model comparison tests (as discussed early in the section on distinguishability). This approach was used by Kuo and colleagues (Kuo, Mohler, Raudenbush, & Earls, 2000) to examine the relationship between demographic risk factors and reports of children's exposure to violence (N=1,880 children and 1,776 parents). The researchers also used the traditional method of conducting analyses separately on fathers' and children's reports and found the results for individual parameter estimates to be very similar. However, it is only possible to statistically test for the differences between informants using the MLM approach, as the two reports must be modeled simultaneously.

Conducting similar analyses is not feasible using the indistinguishable model, as that model does not provide separate parameter estimates of the effects of a couple-level (Level 2) predictor on the two partners' reports (as the two partners are not distinguished). The APIM model could, however, be used to examine differential effects of characteristics that vary for individuals. For example, one could examine the effects of individuals' own characteristics and their partners' characteristics on individuals' reports.

An alternate approach for distinguishable dyads is to examine discrepancies between the reports of the two dyad members (Lyons, Zarit, Sayer, & Whitlach, 2002). Coley and Morris (2002) use this approach to examine discrepancies in mothers' and fathers' reports of father involvement in 228 low-income families. Specifically, reports of the outcome are regressed onto dummy indicators for the mother (–0.5) and father (0.5).

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{indicator}) + r_{ij}. \qquad (20.9)$$

In this model, the intercept represents the *average* of the two parents' reports of father involvement, and the slope represents the *discrepancy* between the two reports, as there is exactly 1.0 unit between indicators. Predictors for the average and the discrepancy can then be added at Level 2. Coley and Morris (2002) found that parental conflict, fathers' nonresidence, and fathers' age, as well as mothers' education and employment, predicted larger discrepancies between fathers' and mothers' reports. Use of the discrepancy approach, however, requires the ability to differentiate between dyad members.

Examining reports from multiple informants is just one of the areas in which there have been recent advances in MLM approaches to dyadic data analysis. Other areas include the dyadic analysis of diary data (Bolger & Shrout, 2007), issues in interpreting cross-level interactions in dyadic models (West et al., 2008), and the use of simulations to conduct accurate power analyses for complex MLM (and SEM) models such as those for dyads (Muthén & Muthén, 2002).

Limitations of Dyadic Multilevel Modeling

Limitations Due to Small Number Per Family

While multilevel modeling provides a useful method for examining family data, it also has important limitations. Most importantly, MLM is a large sample statistical approach; it is at its best when examining a large number of groups (like families) with a large number of individuals per group. Having too few groups or too few individuals per group (as with dyads) presents a power issue as there is not enough information to reliably detect effects and can lead to a lack of precision in certain parameter estimates (Maas & Hox, 2005; Raudenbush, 2008).

Number of Families Required

Given the limited number of individuals in families and dyads, a large number of groups (at least 100) are required to obtain accurate estimates of the fixed effects, such as the intercept, rate of change and the predictors, as well as their standard errors (Raudenbush, 2008). While there are alternative estimation procedures that provide more accurate estimates when there are a small number of groups at highest level (Level 2 for the models presented here) with many people per group, these cannot address the problem of the small number of individuals per dyad.

While having a sample of at least 100 dyads will provide accurate parameter estimates of the fixed effects and their standard errors, other parameter estimates lack precision due to the small number of individuals per dyad: specifically the estimates of the Level-2 variance components may be inaccurate (e.g., the amount of variability between dyads; Raudenbush, 2008). Consequently, researchers should not rely on statistical tests regarding the amount of variability when deciding whether or not to enter predictors into their model. In addition, the MLM estimates of individual scores for each dyad (the estimated Bayesian coefficients) are unreliable. This is of greatest concern with cross-sectional models, as well-fitting longitudinal models with assessments across multiple time points allow for more accurate estimation.

Noncontinuous Outcomes

Another important limitation to having a small number of individuals per family or dyad is that these models should only be applied to the analysis of continuous outcomes (Raudenbush, 2008). When examining outcomes that are not continuously distributed, such as categorical or count data, MLM cannot provide accurate estimates when there are only a few number of individuals per group, even if there are a large number of these small groups. When there are a large number of dyads, SEM would be the preferred approach to analyzing dichotomous or count data (or any other outcome which requires a link function to transform the outcome into a normal distribution). Unfortunately, there are no published studies comparing the reliability of estimates provided using different approaches (e.g., MLM, cluster-adjusted standard errors, SEM) to dealing with the dependence of dyadic data in the face of small sample sizes. Consequently, it is unclear which approaches should be recommended to researchers confronting these problems.

The Same Number of Individuals Per Family

A limitation specific to dyadic (or triadic) MLM models is the need to have the same number of individuals in each family. While the basic organizational, cross-sectional model can be used to examine reports from a variable number of family members, such as families with different numbers of siblings, dyadic models are more restricted. Dyadic models are designed to examine pairs of individuals. This limitation means that you can only analyze data in which there are two reporters from each family (although the data from some of the second reporters can be missing). Consequently, the dyadic model precludes the analysis of data from both coupled and single parents. For example,

the longitudinal model for indistinguishable dyads could not be used to examine a sample of lesbian parents that included both single and coupled lesbian mothers. While the dyadic models for indistinguishable dyads can easily handle couple data, they cannot accommodate a combination of coupled and single parents. Note that examining outcomes from both single and coupled parents is distinct from examining data from couples and having missing data from some partners. While multilevel modeling can accommodate missing data on the outcome, it assumes that these data are missing at random (MAR).

Future Directions

While there have been many important recent advances in the use of MLM (and SEM) for the analysis of dyadic data, particularly in the indistinguishable case, much more work is needed. To better understand the strengths and limitations of these models, studies are needed to examine the extent to which estimates may be affected by the small number of members per dyad. Currently, the smallest within-group size examined in the published literature contained 5 individuals per group, while dyads only have 2 individuals per group (Maas & Hox, 2005). While MLM has become the norm for dyadic data analysis, some researchers contend that the lack of precision in the estimates of the standard errors is sufficient to call the entire approach into question; these researchers tend to prefer the use of SEM approaches to dyadic data. In the absence of additional studies in this area, researchers may best be guided by the guidelines that Raudenbush (2008) presents in his chapter, "Many Small Groups." Raudenbush clearly articulates when MLM approaches to examining small groups such as families and dyads are appropriate (i.e., a large number of groups, continuous outcomes, focus on fixed effects), and where specific applications are inappropriate (i.e., small number of groups, dichotomous or count outcomes, a focus on Level-2 random effects, estimated Bayesian coefficients for individuals).

Given that a great deal of research on LGBT parents and families is conducted on samples with fewer than 100 families, MLM modeling (and SEM) will not provide an appropriate method to address the questions of many researchers. There is great need for a clear articulation of the most appropriate methods for dealing with the dependent data in small samples. While Raudenbush (2008) clearly explains the limitations of MLM approaches to examining small groups such as families and dyads, he fails to indicate appropriate alternative approaches where MLM is not appropriate. While there are good recent papers introducing multilevel modeling approaches to dyadic data (e.g., Atkins, 2005; Kashy et al., 2008; Sayer & Klute, 2005), as well as general recommendations for researchers gathering dyadic data (Ackerman, Donnellan, & Kashy, 2011), there is a need for a paper on the state-of-the-art practices for examining such data in small samples.

While there are still many areas requiring further development in the application of multilevel modeling to the examination of family data, the most important need in the area of LGBT research is the need to make existing methods more available to researchers. To use MLM approaches to dyadic data analysis, researchers must learn both the basics of MLM and the ins and outs of dyadic models. While multilevel modeling is increasingly being taught in departments such as family studies, human development, and psychology, training is still unavailable to students in many programs. Most researchers who study LGBT couples, parents, and families will need to seek out training beyond the courses they were offered in their graduate program. There are training workshops in MLM available across the country (see Appendix A for current programs offering dyadic workshops using MLM). Only a small number of these, however, specifically address approaches for dyads in which members are indistinguishable (most notably David Kenny's workshop). There are however many useful resources available on the web (see Appendix B).

If researchers who study LGBT couples, parents, and families are unable to employ the statistical methods appropriate for their data and research questions, it hinders the development of the field. Researchers who are unfamiliar with the appropriate statistical methods to analyze

their data are unable to publish, particularly in the leading journals in fields such as family studies, psychology, and others. In addition, they are often unable to capitalize on the richness of their datasets. Currently, the greatest need in this area is to provide statistical training in methods such as multilevel modeling to junior and senior researchers and to facilitate collaborations between LGBT researchers who lack this training and both established and emerging methodologists in the field of dyadic data analysis.

Appendix A. Organizations Providing Workshops on Multilevel (and Other) Modeling Approaches to Dyadic Data Analysis

Data Analysis Training Institute of Connecticut (DATIC; U of Connecticut) http://datic.uconn.edu/

Center for Research on Families (U of Mass) http://www.umass.edu/family/methodology

ICPSR Summer Program in Quantitative Methods of Social Research (U of Michigan) http://www.icpsr.umich.edu/icpsrweb/content/sumprog/about.html

Note: Many of the foremost scholars in the field of dyadic data analysis have offered workshops through the above or other institutions (e.g., David Kenny, Deborah Kashy, Nial Bolger, Jean-Philippe Laurenceau, and Aline Sayer).

Appendix B. Online Resources for Dyadic Data Analysis

Overview of Dyadic Data Analysis http://www.davidakenny.net/dyad.htm

Materials and Syntax to Accompany Kenny et al. (2006), Dyadic Data Analysis http://www.davidakenny.net/kkc/kkc.htm

Introductory Materials on Dyadic Data Analysis http://www.umass.edu/family/methodology/ncfr.htm

Videos Introducing Dyadic Analysis and Explaining Dyadic Modelling Approaches by Bolger and Laurenceau http://methodology.psu.edu/training/mcsi10media

Mulilevel Listserv http://www.nursing.manchester.ac.uk/learning/staff/mcampbell/multilevel.html

References

Ackerman, R. A., Donnellan, M., & Kashy, D. A. (2011). Working with dyadic data in studies of emerging adulthood: Specific recommendations, general advice, and practical tips. In F. D. Fincham & M. Cui (Eds.), *Romantic relationships in emerging adulthood* (pp. 67–97). New York, NY: Cambridge University Press.

Atkins, D. (2005). Using multilevel models to analyze couple and family treatment data: Basic and advanced issues. *Journal of Family Psychology, 19*, 86–97. doi:10.1037/0893-3200.19.1.98

Atkins, D. C., Klann, N., Marín, R. A., Lo, T. Y., & Hahlweg, K. (2010). Outcomes of couples with infidelity in a community-based sample of couple therapy. *Journal of Family Psychology, 24*, 212–216. doi:10.1037/a0018789

Bailey, J., Kim, P. Y., Hills, A., & Linsenmeier, J. W. (1997). Butch, femme, or straight acting? Partner preferences of gay men and lesbians. *Journal of Personality and Social Psychology, 73*,960–973. doi:10.1037/0022-3514.73.5.960

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 and Social Psychology, 64*,794–806. doi:10.1037/0022-3514.64.5.794

Bengtson, V. L., & Allen, K. R. (1993). The life course perspective applied to families over time. In P. G. Boss, W. J. Doherty, R. LaRossa, W. R. Schumm, S. & K. Steinmetz (Eds.), *Sourcebook of family theories and methods: A contextual approach* (pp. 469–504). New York, NY: Plenum Press.

Bolger, N., & Shrout, P. E. (2007). Accounting for statistical dependency in longitudinal data on dyads. In T. D. Little, J. A. Bovaird, & N. A. Card (Eds.), *Modeling contextual effects in longitudinal studies* (pp. 285–298). Mahwah, NJ: Lawrence Erlbaum Associates.

Brincks, A. M., Feaster, D. J., & Mitrani, V. B. (2010). A multilevel mediation model of stress and coping for women with HIV and their families. *Family Process, 49*, 517–529. doi:10.1111/j.1545-5300.2010.01337.x

Bronfenbrenner, U. (1988). Interacting systems in human development. In N. Bolger, A. Caspi, G. Downey, & M. Moorehouse (Eds.), *Persons in context: Developmental processes* (pp. 25–49). New York, NY: Cambridge University Press.

Campbell, L. J., & Kashy, D. A. (2002). Estimating actor, partner, and interaction effects for dyadic data using PROC MIXED and HLM5: A user-friendly guide.

Personal Relationships, 9, 327–342. doi:10.1111/1475-6811.00023

Christensen, A., Atkins, D. C., Yi, J., Baucom, D. H., & George, W. H. (2006). Couple and individual adjustment for 2 years following a randomized clinical trial comparing traditional versus integrative behavioral couple therapy. *Journal of Consulting and Clinical Psychology, 74*, 1180–1191. doi:10.1037/0022-006X.74.6.1180

Claxton, A., O'Rourke, N., Smith, J. Z., & DeLongis, A. (2012). Personality traits and marital satisfaction within enduring relationships: An intra-couple concurrence and discrepancy approach. *Journal of Social and Personal Relationships, 29*, 375–396.

Coley, R., & Morris, J. (2002). Comparing father and mother reports of father involvement among low-income minority families. *Journal of Marriage and Family, 64*, 982–997. doi:10.1111/j.1741-3737.2002.00982.x

Cook, W. L., & Kenny, D. A. (2005). The actor-partner interdependence model: A model of directional effects in developmental studies. *International Journal of Behavioral Development, 29*, 101–109. doi:10.1080/01650250444000405

Cox, M. J., & Paley, B. (1997). Families as systems. *Annual Review of Psychology, 48*, 243–267. doi:10.1146/annurev.psych.48.1.243

Fergus, S., Lewis, M. A., Darbes, L. A., & Kral, A. H. (2009). Social support moderates the relationship between gay community integration and sexual risk behavior among gay male couples. *Health Education & Behavior, 36*, 846–859. doi:10.1177/1090198108319891

Georgiades, K., Boyle, M. H., Jenkins, J. M., Sanford, M., & Lipman, E. (2008). A multilevel analysis of whole family functioning using the McMaster family assessment device. *Journal of Family Psychology, 22*, 344–354. doi:10.1037/0893-3200.22.3.344

Goldberg, A. E. (2010). *Lesbian and gay parents and their children: Research on the family life cycle*. Washington, DC: American Psychological Association

Goldberg, A. E., & Perry-Jenkins, M. (2007). The division of labor and perceptions of parental roles: Lesbian couples across the transition to parenthood. *Journal of Social and Personal Relationships, 24*, 297–318. doi:10.1177/0265407507075415

Goldberg, A. E., & Sayer, A. G. (2006). Lesbian couples' relationship quality across the transition to parenthood. *Journal of Marriage and Family, 68*, 87–100. doi:10.1111/j.1741-3737.2006.00235.x

Goldberg, A. E., & Smith, J. Z. (2008a). The social context of lesbian mothers' anxiety during early parenthood. *Parenting: Science & Practice, 8*, 213–239. doi:10.1080/15295190802204801

Goldberg, A. E., & Smith, J. Z. (2008b). Social support and well-being in lesbian and heterosexual preadoptive couples. *Family Relations, 57*, 281–291. doi:10.1111/j.1741-3729.2008.00500.x

Goldberg, A. E., & Smith, J. Z. (2009a). Perceived parenting skill across the transition to adoptive parenthood: A study of lesbian, gay and heterosexual couples. *Journal of Family Psychology, 23*, 861–870. doi:10.1037/a0017009

Goldberg, A. E., & Smith, J. Z. (2009b). Predicting non-African American lesbian and heterosexual preadoptive couples' openness to adopting an African American child. *Family Relations, 58*, 346–360. doi:10.1111/j.1741-3729.2009.00557.x

Goldberg, A. E., & Smith, J. Z. (2011). Stigma, support and mental health: Lesbian and gay male couples across the transition parenthood. *Journal of Counseling Psychology, 58*, 139–150. doi:10.1037/a0021684

Goldberg, A. E., Smith, J. Z., & Kashy, D. (2010). Preadoptive factors predicting lesbian, gay and heterosexual couples relationship quality across the transition parenthood. *Journal of Family Psychology, 24*, 221–232. doi:10.1037/a0019615

Griffin, D., & Gonzalez, R. (1995). Correlational analysis of dyad-level data in the exchangeable case. *Psychological Bulletin, 118*, 430–439. doi:10.1037/0033-2909.118.3.430

Jenkins, J. M., Cheung, C., Frampton, K., Rasbash, J., Boyle, M. H., & Georgiades, K. (2009). The use of multilevel modeling for the investigation of family process. *European Journal of Developmental Science, 3*, 131–149.

Kashy, D. A., Donnellan, M. B., Burt, S. A., & McGue, M. (2008). Growth curve models for indistinguishable dyads using multilevel modeling and structural equation modeling: The case of adolescent twins' conflict with their mothers. *Developmental Psychology, 44*, 316–329. doi:10.1037/0012-1649.44.2.316

Kashy, D. A., & Kenny, D. A. (2000). The analysis of data from dyads and groups. In H. Reis & C. M. Judd (Eds.), *Handbook of research methods in social psychology* (pp. 451–477). New York, NY: Cambridge University Press

Kenny, D. A., & Cook, W. (1999). Partner effects in relationship research: Conceptual issues, analytic difficulties, and illustrations. *Personal Relationships, 6*, 433–448. doi:10.1111/j.1475-6811.1999.tb00202.x

Kenny, D. A., & Judd, C. M. (1986). Consequences of violating the independence assumption in analysis of variance. *Psychological Bulletin, 99*, 422–431. doi:10.1037/0033-2909.99.3.422

Kenny, D., Kashy, D., & Cook, W. (2006). *Dyadic data analysis*. New York, NY: Guilford Press

Kenny, D. A., & Ledermann, T. (2010). Detecting, measuring, and testing dyadic patterns in the actor–partner interdependence model. *Journal of Family Psychology, 24*, 359–366. doi:10.1037/a0019651

Kretschmer, T., & Pike, A. (2010). Associations between adolescent siblings' relationship quality and similarity and differences in values. *Journal of Family Psychology, 24*, 411–418. doi:10.1037/a0020060

Kuo, M., Mohler, B., Raudenbush, S. L., & Earls, F. J. (2000). Assessing exposure to violence using multiple informants: Application of hierarchical linear model. *Journal of Child Psychology and Psychiatry, 41*, 1049–1056. doi:10.1111/1469-7610.00692

Kurdek, L. A. (1997). The link between facets of neuroticism and dimensions of relationship commitment:

Evidence from gay, lesbian, and heterosexual couples. *Journal of Family Psychology, 11*, 503–514. doi:10.1037/0893-3200.11.4.503

Kurdek, L. A. (1998). Relationship outcomes and their predictors: Longitudinal evidence from heterosexual married, gay cohabiting, and lesbian cohabiting couples. *Journal of Marriage and the Family, 60*, 553–568. doi:10.2307/353528

Kurdek, L. A. (2003). Differences between gay and lesbian cohabiting couples. *Journal of Social and Personal Relationships, 20*, 411–436. doi:10.1177/02654075030204001

Kurdek, L. A. (2008). Change in relationship quality for partners from lesbian, gay male, and heterosexual couples. *Journal of Family Psychology, 22*, 701–711. doi:10.1037/0893-3200.22.5.701

Kurdek, L. A., & Schmitt, J. P. (1986a). Interaction of sex role self-concept with relationship quality and relationship beliefs in married, heterosexual cohabitating, gay, and lesbian couples. *Journal of Personality and Social Psychology, 51*, 365–370. doi:10.1037/0022-3514.51.2.365

Kurdek, L. A., & Schmitt, J. P. (1986b). Relationship quality of partners in heterosexual married, heterosexual cohabitating, and gay and lesbian relationships. *Journal of Personality and Social Psychology, 51*, 711–720. doi:10.1037/0022-3514.51.4.711

Lyons, K. S., Zarit, S. H., Sayer, A. G., & Whitlach, C. J. (2002). Caregiving as a dyadic process: Perspectives from caregiver and receiver. *Journal of Gerontology: Psychological Sciences, 57B*, 195–204.

Maas, C. J. M., & Hox, J. J. (2005). Sufficient sample size for multilevel modeling. *Methodology, 1*, 86–92. doi:10.1027/1614-2241.1.3.86

Meteyer, K., & Perry-Jenkins, M. (2010). Father involvement among working-class, dual-earner couples. *Fathering: A Journal of Theory, Research, & Practice about Men as Fathers, 8*, 379–403.

Muthén, L. K., & Muthén, B. O. (2002). How to use a Monte Carlo study to decide on sample size and determine power. *Structural Equation Modeling, 9*, 599–620. doi:10.1207/S15328007SEM0904_8

O'Rourke, N., Kupferschmidt, A. L., Claxton, A., Smith, J. Z., Chappell, N., & Beattie, B. L. (2010). Psychological resilience predicts depressive symptoms among spouses of persons with Alzheimer disease over time. *Aging and Mental Health, 14*, 984–993. doi:10.1080/13607863.2010.501063

Olsen, J. A., & Kenny, D. A. (2006). Structural equation modeling with interchangeable dyads. *Psychological Methods, 11*, 127–141. doi:10.1037/1082-989X.11.2.127

Papp, L. M., Goeke-Morey, M. C., & Cummings, E. (2007). Linkages between spouses' psychological distress and marital conflict in the home. *Journal of Family Psychology, 21*, 533–537. doi:10.1037/0893-3200.21.3.533

Papp, L. M., Pendry, P., & Adam, E. K. (2009). Mother-adolescent physiological synchrony in naturalistic settings: Within-family cortisol associations and moderators. *Journal of Family Psychology, 23*, 882–894. doi:10.1037/a0017147

Patterson, C. J., Sutfin, E. L., & Fulcher, M. (2004). Division of labor among lesbian and heterosexual parenting couples: Correlates of specialized versus shared patterns. *Journal of Adult Development, 11*, 179–189. doi:10.1023/B:JADE.0000035626.90331.47

Perry-Jenkins, M., Goldberg, A. E., Pierce, C. P., & Sayer, A. G. (2007). Shift work, role overload, and the transition to parenthood. *Journal of Marriage & Family, 69*, 123–138. doi:10.1111/j.1741-3737.2006.00349.x

Perry-Jenkins, M., Smith, J. Z., Goldberg, A., & Logan, J. N. (2011). Working-class jobs and new parents' mental health. *Journal of Marriage and Family, 73*, 1117–1132. doi:10.1111/j.1741-3737.2011.00871.x

Raudenbush, S. W. (2008). Many small groups. In J. de Leeuw, E. Meijer, J. de Leeuw, & E. Meijer (Eds.), *Handbook of multilevel analysis* (pp. 207–236). New York, NY: Springer. doi:10.1007/978-0-387-73186-5_5

Raudenbush, S. W., Brennan, R., & Barnett, R. (1995). A multivariate hierarchical model for studying psychological change within married couples. *Journal of Family Psychology, 9*, 161–174. doi:10.1037/0893-3200.9.2.161

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods*. Thousand Oaks, CA: Sage.

Raudenbush, S., Bryk, A., & Congdon, R. (2004). *HLM6: Hierarchical linear and nonlinear modeling*. Chicago, IL: Scientific Software International.

Regan, P. C., Medina, R., & Joshi, A. (2001). Partner preferences among homosexual men and women: What is desirable in a sex partner is not necessarily desirable in a romantic partner. *Social Behavior and Personality, 29*, 625–633. doi:10.2224/sbp. 2001.29. 7.625

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

Simpson, L. E., Atkins, D. C., Gattis, K. S., & Christensen, A. (2008). Low-level relationship aggression and couple therapy outcomes. *Journal of Family Psychology, 22*, 102–111. doi:10.1037/0893-3200.22.1.102

Soliz, J., Thorson, A. R., & Rittenour, C. E. (2009). Communicative correlates of satisfaction, family identity, and group salience in multiracial/ethnic families. *Journal of Marriage and Family, 71*, 819–832. doi:10.1111/j.1741-3737.2009.00637.x

West, T. V., Popp, D., & Kenny, D. A. (2008). A guide for the estimation of gender and sexual orientation effects in dyadic data: An actor-partner interdependence model approach. *Personality & Social Psychology Bulletin, 34*, 321–336. doi:10.1177/0146167207311199

Willett, J. B. (1989). Some results on reliability for the longitudinal measurement of change: Implications for the design of studies of individual growth. *Educational and Psychological Measurement, 49*, 587–602. doi:10.1177/001316448904900309

Woody, E., & Sadler, P. (2005). Structural equation models for interchangeable dyads: Being the same makes a difference. *Psychological Methods, 10*, 139–158. doi:10.1037/1082-989X.10.2.139