

The Actor-Partner Interdependence Model for Categorical Dyadic Data:

A User-friendly Guide to GEE

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Abstract

The actor-partner interdependence model (APIM) has been widely used for the analysis of pairs of individuals who interact with each other. The goal of this paper is to detail in a non-technical way how the APIM for binary or count outcomes can be implemented and how actor and partner effects can be estimated using generalized estimating equations (GEE) methodology. Both SPSS- and SAS-syntax needed to estimate the model and the interpretation of the output are illustrated using data from a study exploring the effect of satisfaction with the relationship before the break-up on unwanted pursuit behavior after the break-up in formerly married partners. The use of this GEE method will allow researchers to test a wide array of research hypotheses.

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When two people interact in a relationship, the outcome of each person can be affected by both his or her own inputs and his or her partner's inputs. The actor-partner interdependence model (APIM), offers an appealing approach to model such dyadic data (Kenny, Kashy, & Cook, 2006). This model is perfectly suited when the same measurements are taken in both members of the dyads and naturally allows for interdependence. Indeed, it allows one to simultaneously study the influence of a person's own predictor variable on his or her own outcome variable, which is called *the actor effect*, and on the outcome variable of the partner, which is called *the partner effect*, while allowing for non-independence in the two persons' outcomes. Typically, two types of dyads are considered. Dyads are called *distinguishable* when the two persons from each dyad can be ordered in the same way (e.g., in heterosexual couples, persons can be ordered or distinguished by gender). Dyads are *indistinguishable* when no ordering of persons exists within the dyad (e.g., gay or lesbian couples). For example, in an APIM study of indistinguishable dyad members, Markey and Markey (2012) found in a sample of 72 lesbian couples that higher levels of relationship quality were reported by participants who were warm and submissive (actor effect) and those who had partners who possessed these characteristics (partner effect).

Figure 1 shows a graphical presentation of the APIM with two distinguishable dyad members and an X and Y variable for each. The variables X_1 and X_2 represent the predictor variables of persons 1 and 2 of a dyad, respectively, whereas Y_1 and Y_2 represent the outcome variables for the two members. The model contains two actor effects a_1 and a_2 (represented by the horizontal arrows), and two partner effects p_{12} and p_{21} (represented by the diagonal arrows). The curved arrow on the left of Figure 1 reflects the correlation between the predictor variables, whereas the one on the right represents the correlation between the

residual terms (i.e., unexplained variance). While the primary focus in the APIM is typically on estimating the actor and partner effects, these unknown sources of non-independence must still be accounted for.

From interval level dyadic data to categorical data

Most relationships researchers are cognizant of the problems resulting from ignoring this non-independence. When data are measured on the *interval level*, multilevel modeling (MLM), also referred to as hierarchical linear modeling or mixed models, has been shown to be a useful technique for the estimation of actor and partner effects in dyadic data (Kenny et al., 2006) while accounting for the non-independence. The use of such models is limited though to outcomes measured at the interval level. In practice, however, a dyadic researcher might be faced with non-interval outcomes such as *binary* (“yes” or “no”) or *count* outcomes. Whisman, Uebelacker and Settles (2010), for example, evaluated the effect of marital distress on having metabolic syndrome or not, a binary outcome. Binary outcomes are typically analyzed using logistic regression models when the outcome observations are independent. However due to the non-independence of outcomes in dyads, one needs to go beyond those logistic regression models. Finkel et al. (2012) explored how dispositional aggressiveness in couples predicts the number of intimate partner violence perpetrations, a count outcome. For such count outcomes, linear regression based on ordinary least squares techniques is usually not appropriate, and a regression model that does not assume that the dependent variable has a normal distribution should be used instead (Atkins & Gallop, 2007).

The goal of this paper is to provide the relationship researcher with effective ways to estimate actor and partner effects when outcomes in dyads are categorical (i.e., binary or count outcomes). More specifically, we will present estimation based on a generalized estimating equations (GEE) approach. The latter can be viewed as an extension of the logistic and count regression model for independent data that accounts for nonindependence. To focus

ideas, we first introduce our illustrating example. Next we revisit the APIM analysis using the MLM for normally distributed outcomes. Then we summarize earlier proposals extending these multilevel approaches for outcomes not measured at the interval level and contrast these approaches in a more technical way with the GEE-methodology that we want to introduce in this paper. Using our illustrating example, we provide a non-technical description how the latter can easily be implemented in standard software packages and how the associated output can be interpreted.

Illustrating Example: Unwanted Pursuit Behavior in Ex-Couples

To illustrate methods of analyzing the APIM when outcomes are dichotomies or counts, we will use data from the Interdisciplinary Project for the Optimization of Separation Trajectories conducted in Flanders (IPOS; www.scheidingsonderzoek.ugent.be), which organized a large-scale recruitment of divorcing partners in Flanders between March 2008 and March 2009. Although the IPOS study was designed to recruit individual ex-partners, the sample coincidentally included 33 heterosexual ex-couples with valid scores on the measures of interest. To enlarge statistical power, a second recruitment was organized between December 2010 and March 2011 (in the court of Ghent), this time explicitly targeted at ex-couples, yielding 13 additional ex-couples who completed the questionnaires of interest.

These 46 heterosexual ex-couples responded to an adapted version of the Relational Pursuit-Pursuer Short Form (RP-PSF; Cupach & Spitzberg, 2004), which measures the extent of UPB-perpetrations towards the ex-partner since the break-up. The total of 28 RP-PSF items (ranging from “leaving unwanted gifts” to “threatening to hurt yourself”), each measured on a 5-point Likert scale (from 0 = never to 4 = over 5 times), was as an overall index of perpetration (with higher scores indicating more frequent perpetrations of unwanted pursuit tactics). The 28-item measure was reliable in this study: Cronbach’s $\alpha = .81$. A participant who

answered “never” to all these 28 items will have an UPB-outcome equal to 0, while a participant who answered “over 5 times” to “leaving unwanted gifts” and “never” to all other items will have an UPB-total equal to 4. A participant who answered “over 5 times” to all items will have the maximum score of 112 (the maximum score observed in the sample was 26).

Many predictors for the UPB-outcome were measured in the original study (De Smet, Loeys, & Buysse, 2013). Here we will only analyze the impact of the actor’s and partner’s pre-breakup level of relationship satisfaction. Relationship satisfaction was measured using a total of five items from a Dutch version of the Investment Model Scale (IMS; Rusbult, Martz, & Agnew, 1998), with the wording in the scale modified such that ex-partners focused on the total period of their past relationship (e.g., “During the time I was together with my ex-partner, our relationship made me very happy”). Responses to these five items were based on a 9-point Likert scale (0 = *do not agree at all* - 8 = *completely agree*). In the current sample, the scale performed well in terms of internal consistency: $\alpha = .93$. Relationship satisfaction scores were centered using the grand mean (i.e., the sample mean of all satisfaction scores ignoring the distinguishing variable, in this case ignoring gender; Kenny et al., 2006, p. 94).

We will explore in this sample of 46 heterosexual ex-couples the association between relationship satisfaction before the break-up and unwanted pursuit behavior (UPB) after the break-up. As we are dealing with heterosexual ex-couples, dyad members are distinguishable by gender in our case. One may be interested here in knowing whether the level of relationship satisfaction in men (X_1 in Figure 1) predicts their enactment of UPB towards their ex-partner (Y_1 in Figure 1), and similarly whether the women’s relationship satisfaction (X_2 in Figure 1) predicts the women’s UPB (Y_2 in Figure 1). These are the actor effects a_1 and a_2 . In addition, the level of satisfaction of men may predict the perpetration of UPB by their ex-wives, and the level of satisfaction of women may predict the perpetration of UPB by their ex-

husbands. These are, respectively, the partner effects p_{12} and p_{12} in Figure 1. Primary interest lies in the actor and partner effects of relationship satisfaction on the *frequency* of perpetrated post-divorce UPBs, so we should look at the variable that *counts* these behaviors. Similarly, one may simply be interested in the effects of relationship satisfaction on the presence or absence of UPB, a binary outcome. Although such dichotomization of frequency data is not recommended (MacCallum, Zhang, Preacher, & Rucker, 2002), it is presented here for illustrative purposes only.

Multilevel Models for Outcomes Measured at the Interval Level

For pedagogical purposes, consider just the men in our sample of 46 ex-couples, and assume some fictive outcome measured at the interval level, let's say emotional distress. To assess the impact of actor and partner relationship satisfaction (denoted by SAT_A and SAT_P, respectively) as predictors of this outcome in men (denoted by Y_M), we can assume the following linear regression model:

$$E[Y_M] = \beta_{0M} + \beta_{1M} * SAT_A + \beta_{2M} * SAT_P \quad (1)$$

In model (1), the mean outcome is expressed as a function of the covariates SAT_A and SAT_P. The parameter β_{1M} captures the effect of the man's own relationship satisfaction on his emotional distress (i.e., the actor effect), while β_{2M} reflects the effect of the wife's relationship satisfaction on her ex-husband's emotional distress (i.e., the partner effect). When fitting such linear regression model, we are further assuming that the outcomes (or more precisely, the residuals from the model) are independent and normally distributed with constant variance σ^2_M .

Similarly, we can model the women's outcome Y_F , assuming a linear regression model

$$E[Y_F] = \beta_{0F} + \beta_{1F} * SAT_A + \beta_{2F} * SAT_P, \quad (2)$$

where now SAT_A corresponds to the woman's relationship satisfaction and SAT_P to the man's relationship satisfaction. Here too the residuals are supposed to follow a normal distribution with constant variance σ_F^2 .

Simultaneous modeling of outcomes using MLM

Rather than estimating the actor and partner effects in men and women separately, the APIM aims to estimate models (1) and (2) simultaneously. If the variable Y now represents the outcome of either a man or woman, one can model the mean outcome as

$$E[Y] = \beta_{0F} * \text{FEMALE} + \beta_{0M} * \text{MALE} + \beta_{1F} * \text{FEMALE} * \text{SAT_A} + \beta_{1M} * \text{MALE} * \text{SAT_A} \\ + \beta_{2F} * \text{FEMALE} * \text{SAT_P} + \beta_{2M} * \text{MALE} * \text{SAT_P}, \quad (3)$$

with FEMALE=1 if a woman, and else 0; and MALE=1 if a man, and else 0. This formulation is called the two-intercept model (Kenny et al., 2006), because it has two intercepts: one for the women and one for the men. This model simply combines models (1) and (2) into a single model, with the interpretation of the parameters remaining the same as before. That is, the parameter β_{1F} captures the actor effect of relationship satisfaction in women, while β_{1M} captures the actor effect in men. Similarly, β_{2F} reflects the effect of the man's relationship satisfaction on the outcome in the woman, while β_{2M} captures the partner effect in men. The outcomes of the man and his ex-wife in model (3) are typically correlated, and so the independence assumption of the simple linear regression model no longer holds. However, one can use multilevel (or mixed models) approaches instead. These methods take non-independence into account. Campbell and Kashy (2002) provide a clear and helpful guide on the implementation of linear mixed models in SAS using PROC MIXED (or alternatively in HLM) for the estimation of actor and partner effects in the APIM. In their exposition the REPEATED statement is used to indicate the clustering; that is, the set of outcome variables

that are non-independent. The corresponding SPSS-syntax for model (3) is presented below (see Kenny et al., 2006)

MIXED

Y WITH MALE FEMALE SAT_A SAT_P|NOINT

/FIXED= FEMALE MALE FEMALE*SAT_A MALE*SAT_A FEMALE*SAT_P
MALE*SAT_P

/REPEATED GENDER| SUBJECT (ID) COVTYPE(CSH)

The repeated statement identifies GENDER as the distinguishing variable and ID, identifying dyad membership, as the variable within which outcomes are clustered or nonindependent.

The COVTYPE(CSH) stands for “compound symmetry heterogeneous” which indicates that the residual variances for the male and female outcomes can be unequal and that the correlation between them will be tested. More specifically, this implementation assumes that the outcomes Y_M and Y_F (more precisely, the corresponding residuals obtained after removing the effect of the predictors) are observations from a bivariate normal distribution with variances σ_M^2 and σ_F^2 , respectively, and a correlation ρ that can take any value between -1 and 1. If the covariance type is specified as COVTYPE(CS), it is assumed that the residual variances for the dyad members are equal, i.e. $\sigma_M^2 = \sigma_F^2$). This specification is more appropriate when dyad members are indistinguishable, but is also part of the test of whether they are empirically distinguishable or not (Gonzalez & Griffen, 1999; Kenny et al., 2006, p. 129). Strictly speaking, only when the variances are specified to be equal, ρ corresponds to the intra-class correlation (ICC), but also in other cases this ρ is sometimes referred to as an ICC. If ρ is positive, high levels in the outcome for men are associated with high levels in the outcome for women. Given the above described implications of the REPEATED statement and its COVTYPE option, it should be clear that the multilevel approach specifies the *joint* distribution of the outcomes within a dyad (more specifically, a bivariate normal distribution

in case of outcomes measured at the interval level). Hence, when specifying such joint distribution one makes assumptions on how the outcomes in men and women vary together (or ‘jointly’). The maximum likelihood method, which is used to estimate the parameters of the multilevel model, fully exploits these distributional assumptions.

Alternatively, one could model the dependence between dyad partners indirectly and have, instead of the REPEATED statement, the following record (Kenny et al., 2006, p. 159)

RANDOM INTERCEPT/ SUBJECT=ID

The random intercept describes the variability between dyads. This random intercept formulation also implies a bivariate normal distribution of the outcomes Y_M and Y_F within a dyad (Loeys & Molenberghs, 2013) but it is more restrictive than the earlier formulation with the REPEATED statement. This is the case because (1) it assumes equal variance in men and women (i.e., $\sigma_M^2 = \sigma_F^2$), and (2) it cannot handle negative non-independence (i.e. the implied ICC is always positive). An example of such negative correlation within dyads is the strictness of parental supervision, where the more extreme in strictness one parent becomes, the more extreme in permissiveness the other parent is likely to become (Cook, 2001). Because of these restrictions, the formulation with the REPEATED statement is typically preferred (Kenny et al., 2006).

Multilevel Models for Categorical Outcomes

Building on the above described linear mixed model (LMM) approach for normally distributed outcomes, it seems very natural to use generalized linear mixed models for non-interval outcomes. While the LMM is an extension of the linear model, the generalized linear mixed model (GLMM) is an extension of the generalized linear model (GLM, Agresti, 2000; Nelder & Wedderburn, 1972). GLMs encompass the well-known logistic regression model for dichotomous outcomes and the Poisson regression model for count outcomes, but GLMs are

only well-suited for the analysis of independent data. In the remainder of this section we will primarily focus on dyadic dichotomous outcomes, but in the illustration we will also discuss the analysis of dyadic count outcomes in more detail.

Binary Outcomes

Many outcomes are dichotomous. The Bernoulli distribution (which is the distribution that is used in the logistic regression models described below) can specify probabilities (denoted \Pr) for such binary outcome, $\Pr(Y=1)=\pi$ and $\Pr(Y=0)=1-\pi$ (in other words, the probability of an outcome equal to one is denoted by the Greek letter π). The mean of a Bernoulli outcome, $E(Y)$, equals π , while its variance equals $\pi(1-\pi)$. So, unlike the normal distribution there is no separate parameter for the variance, but the variance is a function of the mean for the Bernoulli distribution. For example, when tossing a coin, define $Y = 1$ if head comes up and $Y = 0$ when tail comes up. Both realizations are equally likely, i.e., $\Pr(Y=1)=\Pr(Y=0)=0.5$, and the mean, $E(Y)$, equals 0.5 and its variance equals $0.5*0.5=0.25$.

Let's now consider our illustrating example and focus on the outcome of showing at least one UPB or not. As mentioned before, we dichotomized this UPB-count outcome here for illustrative purposes only. In practice, such dichotomization should be avoided (MacCallum et al., 2002). When studying in men only the effect of actor and partner relationship satisfaction on showing UPB or not, one could, for example, use the following logistic regression model:

$$\text{logit}(E[Y_M]) = \beta_{0M} + \beta_{1M} * \text{SAT_A} + \beta_{2M} * \text{SAT_P} \quad (4)$$

where Y_M equals 1 if the man shows UPB towards the ex-partner and 0 if the man shows no UPB. The expectation of Y_M , $E[Y_M]$, equals to the probability of showing UPB in men, let's say π_M . In logistic regression model (4) we are using a link function for π_M , called the logit transformation of π_M , and denoted $\text{logit}(\pi_M)$. This transformation is made because while a

probability can only take values between 0 and 1, the logit of this probability can take any value, and hence there are no restrictions on the right hand side of (4). Using the inverse of the logit function one can derive from model (4) an expression for the probability that a man shows at least one UPB

$$\pi_M = \exp(\beta_{0M} + \beta_{1M} * SAT_A + \beta_{2M} * SAT_P) / (1 + \exp(\beta_{0M} + \beta_{1M} * SAT_A + \beta_{2M} * SAT_P)). \quad (5)$$

This transformation somewhat complicates the interpretation of the parameters. While in a linear model, parameters reflect the effect on the mean of a one-unit increase of the predictor, interpretation of the parameters from a logistic regression model is most easily made in terms of odds (i.e. $\Pr(Y=1)/\Pr(Y=0)$). For example, using expression (5) it follows from model (4) that in men the odds of showing UPB increases (if $\beta_{1M} > 0$) with a factor $\exp(\beta_{1M})$ for each unit increase in the level of relationship satisfaction of the actor. In other words, a positive coefficient in model (4) implies that increasing levels of relationship satisfaction are associated with higher probabilities of showing UPB.

Similarly, one can use a logistic regression model for the actor and partner effects of relationship satisfaction on showing UPB in women.

$$\text{logit}(E[Y_F]) = \beta_{0F} + \beta_{1F} * SAT_A + \beta_{2F} * SAT_P \quad (6)$$

As in the linear case, models (4) and (6) can be combined into a single model too

$$\begin{aligned} \text{logit}(E[Y]) = & \beta_{0F} * FEMALE + \beta_{0M} * MALE + \beta_{1F} * FEMALE * SAT_A + \beta_{1M} * MALE * SAT_A \\ & + \beta_{2F} * FEMALE * SAT_P + \beta_{2M} * MALE * SAT_P \end{aligned} \quad (7)$$

Rather than modeling actor and partner effects in men and women separately, we may again look at effects in both men and women simultaneously. Here too, one cannot simply use logistic regression because one needs to deal with the non-independence within dyads. Similar

to the LMM for normally distributed outcomes, the GLMM can in principle deal with correlated categorical outcomes.

Literature Review: from GLMM to GEE

For the specific case of dichotomous dyadic outcomes, McMahon, Pouget, and Tortu (2005) have provided practical guidance on the implementation of proc NLMIXED in SAS to estimate the APIM based on the GLMM. These authors suggested the inclusion of a random intercept to capture the correlation within dyads, using the RANDOM statement (similar as in the above described MIXED procedure). The preferred REPEATED option in the MIXED procedure that allows for the possibility that the correlation is negative is not available in the NLMIXED procedure (Kenny et al., 2006, p. 396). Hence, the appropriateness of their proposal is limited to positively correlated binary outcomes within dyads. These authors did not perform a formal simulation study to assess the statistical properties of their proposal either. Without going into the technical details of the underlying estimation techniques in GLMMs, such a simulation study seems warranted given the approximations that are needed for estimation of the parameters (in contrast to LMMs). Spain, Jackson, and Edmonds (2012) compared in a large simulation study the performance of proc GLIMMIX in SAS (an alternative procedure for fitting multilevel logistic regression models with a random intercept) with HLM in estimating the APIM with a dichotomous dependent variable. For their specific settings, they found that these procedures performed reasonably well in estimating actor and partner effects in sample sizes greater than 100 couples. These authors also mentioned an option in the GLIMMIX procedure similar to the REPEATED statement in the MIXED procedure that allows for negative ICC, but they do not address it in detail.

Recently, Loeys and Molenberghs (2013) compared the GLMM (based on both the GLIMMIX and the NLMIXED procedures) with an approach based on generalized estimating

equations (GEE). Here we summarize their points. These authors found GLMM might not always be the best option for the estimation of actor and partner effects in the APIM and the ICC when the dyadic outcomes are categorical. First, a drawback of the GLMM with a random intercept capturing the interdependence (McMahon et al., 2005; Spain et al., 2012) is that it does not allow for a possible *negative* ICC. Second, their review of APIM-studies revealed that about 25% of the published APIM-studies included less than 60 couples. It is thus important to assess the performance of these procedures in smaller samples too. For example, if a test that there is either no actor effect or partner effect is performed at the 5% significance level, one would expect that there is a 5% chance to reject that hypothesis if the underlying truth in the entire population is that there is indeed no effect. It turns out, however, that by using the traditional GLMM framework such a test for actor or partner effects might be too conservative, especially if the sample size is small. Loeys and Molenberghs (2013) also present two non-standard implementations of the GLMM that can deal with negative correlations (one of these implementations using the equivalent of the REPEATED statement in the GLIMMIX procedure) and they perform better in smaller samples. However, the approximation techniques in the estimation procedure associated with these two implementations tend to produce slightly biased estimates of the actor and partner effects. These authors therefore proposed a GEE-approach (Liang & Zeger, 1986) for the estimation of actor and partner effects in the APIM when dealing with categorical dyadic data.

Generalized Estimating Equations

For a general introduction to the GEE-methodology, we refer the interested reader to Ghisletta and Spini (2004), and for further technical details to Hardin and Hilbe (2003). Here we discuss just the main ideas. Both the GLMM and GEE can be considered as extensions of the generalized linear model. Whereas GLMMs explicitly model the between-dyad variation (by incorporating random effects for example), GEE only requires the user to model the

outcome as a function of actor and partner effects (as in model (7) for example). Because it just uses an expression for the mean, GEE is sometimes called a moment-based method (the mean is sometimes referred to as the first moment and the variance as the second moment of the distribution). In contrast, multilevel or mixed model approaches exploit the full joint distribution. That is, these approaches describe how the outcome in both members of the dyad vary together by explicitly modeling the correlation (the earlier mentioned bivariate normal distribution of the dyadic outcomes in the linear mixed model, for example) and are a likelihood-based methods.

Using an APIM-analysis the relationship researcher may essentially be interested in presenting three quantities: the estimators of the actor and partner effects, their standard errors and the ICC. The GEE procedure primarily focuses on the estimation of the effect of actor and partner effects and rather treats this correlation as a nuisance (Hardin & Hilbe, 2003). Based on the specified model for the outcome, the first step in the GEE-procedure is to treat observations from the same dyad as independent, and to estimate actor and partner effects using a simple GLM. Contrasting the observed and expected (i.e., model-based) outcome, residuals are calculated for each individual. GEE then focuses on the within-dyads similarity of residuals. If one would like to get an idea about the ICC, its estimation can be based on an assumed structure for this similarity of residuals, which is referred to as the *working correlation* matrix. In the dyadic setting there are two possible choices, the residuals can be either uncorrelated (“Independent working correlation”) or correlated (“Unstructured working correlation”). Using the *unstructured* working correlation in the GEE-procedure, GEE will provide an estimate for the ICC¹, but it comes without any associated standard error or test because it is just nuisance parameter.

At first sight, it may seem contradictory to say that GEE only requires the mean, but next also to mention this working correlation. In contrast to misspecification of the random

effects distribution (and its associated implication on the correlation structure) in a multilevel setting, this specification of the working correlation in GEE is not important² for the estimates of the actor and partner effect. Indeed, GEE estimates of the actor and partner effects will still be valid even if this working correlation is misspecified. In contrast, the estimation of the actor and partner effects in the GLMM depends on the specified correlation (by means of the random intercept, for example), and may therefore be invalid in case of misspecification.

So far we have described how the actor and partner effects are estimated using GEE, but also appropriate standard errors of those effects are needed if the relationship researcher wants to perform tests. The standard errors for the actor and partner effects cannot simply be obtained assuming independence. We mentioned in the previous paragraph that a misspecified working correlation structure is not invalidating *the estimates of the actor and partner effects*, but - in contrast - its ‘model-based’ or ‘naive’ *standard errors* that GEE provides, and that rely on the working correlation, are not good under misspecification. Adjustments based on the data (using the specification which individuals belong to the same dyad) can be requested from the GEE-procedure to get appropriate standard errors (these are called the ‘robust’ or ‘empirical’ standard errors). These robust standard errors do not rely on a correct specification of the correlation. It is therefore good practice never to use the naive standard but to only use these robust estimators.

The fact that GEE is a moment-based method also slightly complicates the statistical inference. Indeed, the traditional likelihood-based confidence intervals and p-values that can be used with GLMMs are no longer available. However, as shown by Loeys and Molenberghs (2013) in a simulation study, the robust Wald test derived from the GEE (i.e., the Wald-test obtained by dividing the estimate of the effect by its robust standard error) performs quite well in testing actor and partner effects when the number of dyads is relatively large. When the number of dyads is small, the robust Wald test might be too liberal, and the robust score

test is recommended instead. Based on their simulation study, the Wald test can be typically be used when at least 50 dyads are available.

Implementing a GEE-analysis for the APIM.

Data Structure

First, it is important to discuss the most appropriate way that dyadic data sets should be structured for a GEE-analysis. The best option is to organize the data file according to a pairwise structure (Kenny et al., 2006) as in Table 1. In this file structure there is one record for each individual, but both dyad members' scores occur on each record as well. The first column (ID) is an identifier for the dyad. The second column (GENDER) is the distinguishable variable in our illustrating example, coded as 1 for men and -1 for women. For the two-intercept approach it is convenient to have additional dummy variables for men (MALE) and women (FEMALE). For MALE, men are coded 1 and women 0, and for FEMALE, men are coded 0 and women are coded 1. These dummy variables will then allow to directly estimate the actor and partner effects in males and females using the two-intercept approach. The fifth column (UPB) is the observed UPB-outcome, and the sixth column (UPB2) is a dichotomized version of this variable. Finally, there are two (grand-mean centered) predictor variables: SAT_A (which on a man's record would be the man's score on relationship satisfaction) and SAT_P (which on the man's record would be his ex-wife's score on relationship satisfaction). On the woman's record, SAT_A would be the woman's score on relationship satisfaction and SAT_P would be the man's score on relationship satisfaction.

In the following, we will assess the actor and partner effects of pre break-up relationship satisfaction on showing post break-up UPB or not (the dichotomous outcome UPB2, that is only used here for illustrative purposes) and on the frequency of showing post break-up UPB (the count outcome UPB).

Logistic Regression with a Binary Outcome

In total, 32 of the 92 participants showed at least one UPB towards their ex-partner. We modeled the probability of showing at least one UPB as a function of the relationship satisfaction level of the actor (SAT_A), the satisfaction level of the partner (SAT_P), gender, and allowed for different actor and partner effects in men and women. Using the two-intercept modeling approach, the following logistic regression model links the probability of showing at least one UPB with these predictors:

$$\text{logit}(\text{Pr}(\text{UPB2}=1)) = \beta_{0F} * \text{FEMALE} + \beta_{0M} * \text{MALE} + \beta_{1F} * \text{FEMALE} * \text{SAT_A} + \beta_{1M} * \text{MALE} * \text{SAT_A} + \beta_{2F} * \text{FEMALE} * \text{SAT_P} + \beta_{2M} * \text{MALE} * \text{SAT_P} \quad (8)$$

We can fit such a model using GEE assuming an unstructured working correlation matrix with the following SPSS-syntax (SPSS Statistics version 19):

```
GENLIN UPB2 (REFERENCE=FIRST) WITH MALE FEMALE SAT_A SAT_P

/MODEL FEMALE MALE FEMALE*SAT_A FEMALE*SAT_P MALE*SAT_A
MALE*SAT_P INTERCEPT=NO DISTRIBUTION=BINOMIAL LINK=LOGIT

/CRITERIA ANALYSISTYPE=3(LR)

/REPEATED SUBJECT=ID WITHINSUBJECT=Gender CORRTYPE=UNSTRUCTURED
COVB=ROBUST
```

Because we coded UPB2 as 0 or 1, the REFERENCE=FIRST in the GENLIN-statement indicates that the probability of showing at least one UPB should be modeled. Alternatively, one may want to model the probability of showing no UPB by setting REFERENCE equal to LAST. For the two-intercept approach, the dummy variables for men and women and their interactions with the actor and partner level of relationship satisfaction are included in the

MODEL and no intercept is specified (INTERCEPT=NO). It is indicated that we are analyzing binary data using logistic regression techniques by specifying in the MODEL statement the binomial distribution and logit-link function. The CRITERIA-statement requires the robust score test (ANALYSISTYPE=3 (LR)) to be calculated. Note the somewhat confusing L(ikelihood) R(atio) analysis type option in the SPSS-syntax that appears when the “generalized score” is requested through the interactive menu. The REPEATED-statement treats the individual UPB-outcomes as repeated measures in the dyad (labeled with ID in the SUBJECT-option). These dyads are distinguishable by the variable GENDER (specified in the WITHINSUBJECT-option). The CORRTYPE specifies the unstructured working correlation matrix. Robust standard errors and associated Wald tests are requested by the COVB=ROBUST (instead of the model-based standard errors, which should never be used in practice). The corresponding SAS-syntax (SAS version 9.2) can be found in Appendix 1.

Actor and Partner Effects. The estimated parameters with their robust standard errors for all effects, as well as the p-values from the robust Wald test and score test (denoted by p_{wald} and p_{score} respectively) are shown in Table 2. The advantage of the two-intercept approach is that the actor and partner effects in the men and women can be directly obtained from the output, whereas the other approach (the “interaction approach,” discussed below) requires the interpretation of statistical interaction effects. None of the actor and partner effects are significant at the 5% level in either men or women (note that we observe very similar p-values for the robust Wald test and the robust score test). As we use the logit link in model (8), the final parameters in the output have an interpretation on the log odds ratio scale (i.e., after exponentiating the parameters, one can make interpretations in terms of odds). For example, a one-unit increase in the relationship satisfaction in women, increases the odds of showing at least one UPB towards their ex-husband with a factor $\exp(0.034) = 1.035$. Similarly, a one-unit increase in the relationship satisfaction in their ex-husbands, increases

the odds of showing at least one UPB towards their ex-husband with a factor $\exp(0.021) = 1.021$. In Figure 2 we illustrate how the interpretation of the estimated effects can most conveniently be assessed by graphical presentation. The left panel of Figure 2 shows the probability of perpetrating at least one UPB as a function of relationship satisfaction for male and female actors (at average levels of relationship satisfaction for the partner), respectively. The observed range of the relationship satisfaction scores varied from about 20 points below the sample mean to about 20 points above the sample mean. Whereas increasing relationship satisfaction levels of women before the break-up are associated with an increasing probability of showing at least one UPB towards their ex-partner, the reverse trend is observed in men. These graphs can be obtained by noting that when $\text{logit}(\pi) = \beta$, then $\pi = \exp(\beta)/(1+\exp(\beta))$. So, if one wants to present the actor effect in women at average levels of the partner effect (because we mean-centered all variables, this corresponds to $\text{SAT_P}=0$), one can plot $\exp(-0.618+0.034*\text{SAT_A}) / (1+\exp((-0.618+0.034*\text{SAT_A})))$ as a function of plausible levels of SAT_A (e.g. the range from two standard deviations below the predictor's mean to two standard deviations above the mean). The right panel of Figure 2 shows the probability of showing at least one UPB as a function of the relationship satisfaction level of the partners (at average levels of relationship satisfaction for the actor). Although increasing relationship satisfaction levels of the female ex-partner before the break-up are associated with decreasing probability of showing at least one UPB in men, increasing relationship satisfaction levels of the male ex-partner are associated with increasing probability showing at least one UPB in women. The latter effect is obtained by plotting $\exp(-0.618+0.021*\text{SAT_P}) / (1+\exp((-0.618+0.021*\text{SAT_P})))$ as a function of plausible levels of SAT_P .

Interaction Effects. So far, we have not yet discussed whether the actor and partner effects are significantly different in men and women. While the two-intercept approach nicely provides actor and partner effects for both men and women separately, an alternative

parameterization is needed to assess interactions, which is sometimes referred to as the interaction model (Kenny et al., 2006, p.174). The SPSS-syntax for the GEE-version of the interaction model is as follows:

```
GENLIN UPB2 (REFERENCE=FIRST) WITH SAT_A SAT_P Gender
```

```
/MODEL Gender SAT_A SAT_P Gender*SAT_A Gender*SAT_P INTERCEPT=YES
```

```
DISTRIBUTION=BINOMIAL LINK=LOGIT
```

```
/CRITERIA ANALYSISTYPE=3(LR)
```

```
/REPEATED SUBJECT=ID WITHINSUBJECT=Gender CORRTYPE=UNSTRUCTURED
```

```
COVB=ROBUST
```

In the model statement, the main effect of gender (effect coded as -1 and 1) estimates whether there are differences in showing UPB for men and women, the main effects of SAT_A and SAT_P now assess the overall actor and partner effects across men and women together, while the interactions can be used to see if these effects are significantly different between men and women. Using this formulation, we find no significant interaction effects between gender and the satisfaction level of the actor ($p_{\text{wald}}=.327$; $p_{\text{score}}=.337$), but a marginally significant interaction between gender and the relationship satisfaction level of the partner ($p_{\text{wald}}=.065$; $p_{\text{score}}=.081$). This marginally significant interaction reflects the aforementioned difference in effect of partners' relationship satisfaction level on showing at least one UPB in between men and women: while increasing relationship satisfaction levels of the female ex-partner before the break-up are associated with decreasing probability of showing at least one UPB in men, increasing relationship satisfaction levels of the male ex-partner are associated with increasing probability of showing at least one UPB in women. Finally, we note that,

based on the unstructured working correlation matrix, the estimated ICC between the ex-partners' UPB-outcomes after adjusting for these predictors equals .09.

A Negative Binomial Regression Model for Count Outcome

Rather than looking at the effect on the dichotomized outcome, unwanted pursuit behavior or not, it is better practice to use the actual number of enacted UPBs. While at first sight, one may consider the latter as a measure on the interval level, the distribution of such variables counting certain types of occurrences is typically far from normal. Figure 3 shows the right-skewed distribution of the observed number of UPB-perpetrations. Even after performing a logarithmic transformation the outcome will not be normal. Such count data are therefore frequently modeled using the Poisson distribution (Atkins & Gallop, 2007). The Poisson distribution is characterized by a single parameter μ , which is equal to the mean. The Poisson distribution assumes that the mean is equal to the variance. Yet, with count data, the variance is often larger than the mean (a phenomenon called overdispersion), and as consequence the Poisson distribution may poorly fit the data. This can be seen in Figure 3. Contrasting the observed frequencies with the predicted frequencies under the Poisson assumption in Figure 3 clearly reveals a lack-of-fit (see Loeys, Moerkerke, De Smet & Buysse (2012) for a detailed description of count distributions and associated code to create such figures to assess the fit). The negative binomial distribution, relaxing the Poisson-assumption of equality of the mean and the variance by assuming an additional overdispersion parameter (Hilbe, 2011), yields a much better fit.

For count regression, one typically assumes the following linear relation on the logarithmic scale between the expected number of UPBs and its predictors:

$$\begin{aligned} \log(E(UPB)) = & \beta_{0F} * FEMALE + \beta_{0M} * MALE + \beta_{1F} * FEMALE * SAT_A + \beta_{1M} * MALE * SAT_A \\ & + \beta_{2F} * FEMALE * SAT_P + \beta_{2M} * MALE * SAT_P \end{aligned} \quad (9)$$

This logarithmic transformation of the mean outcome is the default link function for such count regression. While the mean of count outcomes is always larger than zero (i.e. counts are always positive), the logarithm of that mean can take any value. This model should not be confused with the logarithmic transformation on the individual outcomes that is sometimes performed in linear regression models when data are skewed. In the latter approach, the log-transformation is applied on each individual observation first and then the mean is taken over these log-transformed outcomes. Given model (9), the predicted number of UPBs equals $\exp(\beta_{0F} * \text{FEMALE} + \beta_{0M} * \text{MALE} + \beta_{1F} * \text{FEMALE} * \text{SAT_A} + \beta_{1M} * \text{MALE} * \text{SAT_A} + \beta_{2F} * \text{FEMALE} * \text{SAT_P} + \beta_{2M} * \text{MALE} * \text{SAT_P})$. Effects from such count regressions are most easily expressed in terms of a rate. For example, in women the rate of UPBs is increased (if $\beta_{1F} > 0$) with a factor $\exp(\beta_{1F})$ for a one-unit increase in her relationship satisfaction level (at fixed levels of the relationship satisfaction of the partner).

The SPSS-syntax to fit a negative binomial regression using GEE for two-intercept model (9) is as follows:

```
GENLIN UPB WITH MALE FEMALE SAT_A SAT_P
```

```
/MODEL MALE FEMALE FEMALE*SAT_A FEMALE*SAT_P MALE*SAT_A  
MALE*SAT_P INTERCEPT=NO DISTRIBUTION=NEGBIN(MLE) LINK=LOG
```

```
/CRITERIA ANALYSISTYPE=3(LR)
```

```
/REPEATED SUBJECT=ID WITHINSUBJECT=Gender CORRTYPE=UNSTRUCTURED
```

```
COVB=ROBUST
```

This syntax is very similar to the previous one, but now specifies in the model-statement the negative binomial distribution and a log link. The corresponding SAS-syntax can be found in Appendix 1.

Actor and Partner Effects. The estimated actor and partner effects in men and women with their robust standard errors, as well as p-values from the robust Wald test and score test are shown in the last column of Table 2. Interestingly, estimated effects in this count model reveal very similar trends as in the logistic regression model. However, the discrepancy between p-values based on the robust Wald test compared to the p-values from the score test is more substantial now. Based on the robust Wald test, one would conclude significant actor and partner effects in women, and a significant partner effect in men at the 5% significance level, but taking the more conservative approach that was recommended for smaller samples, the score tests did not yield any significant effects.

Interaction Effects. More importantly, using the interaction model approach (needing similar modification to the SPSS-syntax as in the logistic regression model described before) we reach robust conclusions about the interactions: the actor effect in men and women are not significantly different at the 5% significance level ($p_{\text{wald}}=.123$, $p_{\text{score}}=.171$), while the partner effects are different ($p_{\text{wald}}<.001$, $p_{\text{score}}=.036$). It is interesting to note that we found only marginal evidence for the differential partner effect when looking at the binary outcome. Now we now have more convincing evidence using the count outcomes..

The left panel of Figure 4 shows the expected number of UPBs as a function of actor relationship satisfaction level in men and women (at average levels of partner relationship satisfaction), respectively. While in women an increase in their relationship satisfaction level is associated with a higher number of UPBs (for a 10-point increase in satisfaction level, the UPB-rate increases with a factor $\exp(0.047 \cdot 10) = 1.60$, i.e. a 60% increase), the reverse trend is observed in men (for a 10-point increase in satisfaction level, the UPB-rate decreases with a factor $\exp(-0.010 \cdot 10) = 0.90$, i.e. a 10% decrease). The right panel of Figure 4 shows the expected number of UPBs in men and women as a function of the relationship satisfaction level of the ex-wife and ex-husband (at average levels of relationship satisfaction levels),

respectively. While in women increasing relationship satisfaction levels of the ex-husband are associated with higher number of UPBs towards their ex-husband, the reverse trend is observed in men (i.e., men who separated from a more satisfied wife, displayed less UPBs after separation). The latter plots for women and men were obtained by plotting respectively $\exp(0.760+0.056*\text{SAT_P})$ and $\exp(0.175-0.061*\text{SAT_P})$ as a function of varying levels of SAT_P.

These opposite partner effects of relationship satisfaction suggest an interesting contrast pattern. Why do women pursue more satisfied men more intensely and why do men pursue more satisfied women less? A possible explanation may be rooted in gender differences in the central dialectical tension between closeness and autonomy in relationships (De Smet et al. 2013). In general, women desire more closeness and men more autonomy. In the context of our findings, more satisfied men might match women's characteristic desire for closeness, intensifying women's impetus to maintain or re-establish the broken relationship. Additionally, more satisfied attached women are more likely to interfere with men's typical need for autonomy in the relationship, making these women less attractive to pursue.

Finally, it is worth noting that based on the unstructured working correlation matrix from the GEE-procedure, the estimated correlation between the partners' numbers of UPBs after accounting for the effect of predictors (i.e., the actor and partner relationship satisfaction) was -0.07. As mentioned before the GLMM-approach with a random intercept does not allow for such negative ICC. When a multilevel Poisson regression model with random intercept is fitted to these data, the estimated variance of the random intercept is estimated to be zero (further results not shown), leading to the false conclusion that the ICC would be zero. Such misspecification of the covariance structure in the GLMM further entails the risk for unreliable tests for the actor and partner effects (Chavance & Escolana, 2012). As noted earlier, that was one of the reasons, why we prefer the use of GEE opposed to GLMMs.

Indistinguishable Dyads

We have focused on distinguishable dyads in this tutorial as they are encountered more frequently in APIM-analyses, but GEE can easily deal with indistinguishable dyads too. The syntax would only require minor changes. For example, in the SPSS-syntax for the dichotomous outcome, the MODEL statement would not have gender-specific intercepts or gender-specific actor and partner effects, but just a single intercept, a single actor effect, and a single partner effect. Second, the WITHINSUBJECT=GENDER in the REPEATED statement needs to be adapted. SPSS forces you to provide a WITHINSUBJECT variable. In case of indistinguishable dyads one can create a person ID variable that arbitrarily codes one of the subjects as person '1' and the other as person '2' in each dyad. This variable (person) is then used in the WITHINSUBJECT option. Which subject is labeled as '1' and which one as '2' has no impact on the estimation of actor and partner effects in logistic or count regression models using GEE. Moreover, when we specify CORRTYPE = UNSTRUCTURED, the estimate from the resulting working correlation will provide an estimate of the ICC. It is also important to note that the labeling choices have no impact on this ICC (because estimation of the working correlation uses the residuals, which have a mean of zero). As explained in Kenny et al. (2006, p.33), this property of the estimated ICC from GEE is unlike the Pearson correlation of the original measurements. That Pearson correlation depends heavily on who is coded as person 1 and who is coded as person 2.

Discussion and Conclusion

In this paper we have shown how GEE can easily be used for the estimation of actor- and partner-effects in the APIM when the distribution of the outcome variables are not measured at the interval level. Researchers familiar with the interpretation of parameters in

GLMs, like logistic regression models and Poisson regression models, for example, may find this an attractive way to perform their dyadic data analyses.

Like any analytic method GEE has several advantages and disadvantages. On the positive side, we first note its ease of implementation for a large range of outcome types. As illustrated, SPSS and SAS among other software programs can straightforwardly be used to fit the APIM using GEE. Second, the GEE-approach naturally allows for a negative ICC. Using models that only allow for non-negative correlations (like the traditional GLMM with random intercept) may yield the false impression that the ICC is zero (and thus imply that observations are independent) when fitted to dyadic data with negative ICC. Lastly, in contrast to GLMMs, no distributional assumptions are needed for GEE. As long as the model for the mean is correctly specified (i.e., the actor and partner effects are correctly specified) in the models that we discussed here, we obtain appropriate estimates with GEE.

On the negative side, we first note that the GEE-approach is not intended to perform tests about the ICC. Indeed, no standard error is returned from the GEE-procedure as it actually treats the ICC as a nuisance. However, as shown by Loeys and Molenberghs (2013), and in contrast to the multilevel approaches, the GEE procedure can estimate the ICC reasonably well. In addition, we are left with a choice between accepting the statistical significance indicated by the robust score or Wald test. Based on simulation studies, Loeys and Molenberghs (2013) have suggested as a rule of thumb to report the first if the number of dyads is smaller than 50 (and not to rely on the too liberal Wald test in such small samples) and the second for larger samples. When the sample size is large, the discrepancy between the Wald and score test will be smaller.

How large should the sample size of an APIM-study typically be? The sample size should primarily be driven by the power to detect effect sizes of interest and be fixed at the

design stage of the study. With the 46 couples in our illustrating example, and assuming a negative binomial distribution with an overall rate of UPBs that was similar to the one observed in our sample and an ICC reflecting the structure of our data, the presented study had about 90% power (50%, respectively) to detect at the 5% significance level a main actor or partner effect for which a one standard deviation increase in the predictor value leads to a 50% (25%, respectively) increase in the mean number of UPBs. For the interactions, the study had about 80% power to detect an actor or partner effect that is twice as large in men than women, or vice versa. In general, if effect sizes are small-to-moderate, samples size larger than 50 dyads will typically be needed (Kenny et al., 2006, p. 180).

In conclusion, we believe that the GEE approach, by expanding the types of data that can easily be analyzed with the APIM, adds significantly to the toolbox of relationship researchers everywhere. We hope that this paper will guide them for its practical implementation.

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Appendix 1

SAS-CODE

* GEE with binary outcome UPB2: two-intercept model *;

```
proc genmod data=couple descending;
```

```
class ID GENDER;
```

```
model UPB2=MALE FEMALE MALE*SAT_A MALE*SAT_P FEMALE*SAT_A
```

```
FEMALE*SAT_P/noit D=binomial link=logit TYPE3;
```

```
REPEATED SUBJECT=ID/type=UN withinsubject=GENDER corrw;
```

```
run;
```

* GEE with binary outcome UPB2: interaction model *;

```
proc genmod data=couple descending;
```

```
class ID GENDER;
```

```
model UPB2=GENDER SAT_A SAT_P GENDER*SAT_A GENDER*SAT_P/ D=binomial
```

```
link=logit TYPE3;
```

```
REPEATED SUBJECT=ID/type=UN withinsubject=GENDER corrw;
```

```
run;
```

* GEE with count outcome UPB: two-intercept model *;

```
proc genmod data=couple;
```

```
class ID GENDER;
```

```
model UPB=MALE FEMALE MALE*SAT_A MALE*SAT_P FEMALE*SAT_A
```

```
FEMALE*SAT_P/D=nb link=log TYPE3;
```

```
REPEATED SUBJECT=ID/type=UN withinsubject=GENDER corrw;
```

```
run;
```

DYADIC DATA ANALYSIS USING GEE

* GEE with count outcome UPB: interaction model *;

```
proc genmod data=couple;
```

```
class ID GENDER;
```

```
model UPB=GENDER SAT_A SAT_P GENDER*SAT_A GENDER*SAT_P/D=nb link=log  
TYPE3;
```

```
REPEATED SUBJECT=ID/type=UN withinsubject=GENDER corrw;
```

```
run;
```


Footnotes

¹While other choices for the working correlation are available in standard software packages, these other choices (except for the mentioned ‘independent’ working correlation), all are equivalent to the ‘unstructured’ working correlation in the dyadic setting. The estimate for the non-independence from this unstructured working correlation recovers the ICC better than the GLMM procedures do (Loeys & Molenberghs, 2013). Spain et al. (2012) found that estimation of the random effect variance in the GLMM procedure is quite problematic, especially when the number of dyads is smaller than 100. Even if the random effect variances are correctly estimated, the calculation of the ICC from those random effects in the GLMM is a tedious task that is not easily accomplished.

²Technically speaking, one may obtain more efficient estimators when specifying a correct working correlation though. We then borrow strength across dyads to estimate a working correlation matrix and account correctly for the dependence within dyads. The procedure re-iterates between estimating effects and the working correlation until convergence is met.

Table 1. Example of the pairwise data structure.

ID	GENDER	MALE	FEMALE	UPB	UPB2	SAT_A	SAT_P
9	1	1	0	3	1	13.40	0.40
9	-1	0	1	0	0	0.40	13.40
21	1	1	0	2	1	-10.60	8.40
21	-1	0	1	25	1	8.40	-10.60

Table 2. The Actor-Partner Interdependence Model with actor and partner effects for relationship satisfaction in men and women on a binary and count outcome

Effect	Statistic	Logistic regression	Negative binomial regression
Intercept women	β_{0F}	-0.618	0.760
	s.e.	0.339	0.331
	p_{wald}	.068	.022
	p_{score}	.063	.149
Intercept men	β_{0M}	-0.795	0.175
	s.e.	0.335	0.348
	p_{wald}	.018	.614
	p_{score}	.019	.648
Actor in women	β_{1F}	0.034	0.047
	s.e.	0.034	0.024
	p_{wald}	.314	.047
	p_{score}	.329	.151
Actor in men	β_{1M}	-0.011	-0.010
	s.e.	0.034	0.031
	p_{wald}	.746	.738
	p_{score}	.745	.661
Partner in women ^a	β_{2F}	0.021	0.056
	s.e.	0.032	0.021
	p_{wald}	.519	.009
	p_{score}	.513	.157
Partner in men ^a	B_{2M}	-0.055	-0.061
	s.e.	0.031	0.023
	p_{wald}	.079	.008
	p_{score}	.080	.135
ICC		0.09	-0.07

^a. The Partner in women effect reflects the effect from men to women, while the Partner in men effect reflects the effect from women to men.

List of Figures

Figure 1. The APIM model for distinguishable dyads where a is the actor effect and p is the partner effect

Figure 2. The effect of relationship satisfaction level on the probability of showing at least one unwanted pursuit behavior

Figure 3. The observed distribution of the number of unwanted pursuit behaviors in the 46 ex-couples with the expected distribution under a Poisson and negative binomial distribution

Figure 4. The effect of relationship satisfaction level on the expected number of unwanted pursuit behaviors

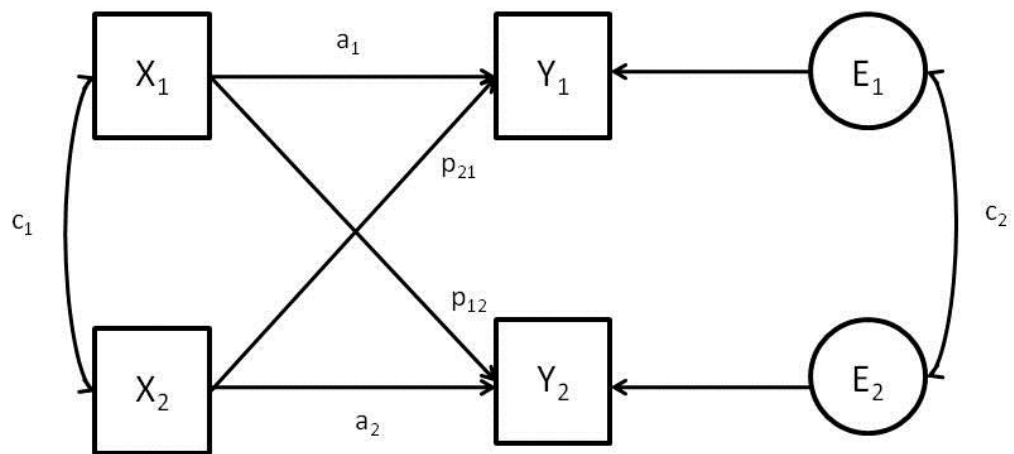


Figure 1

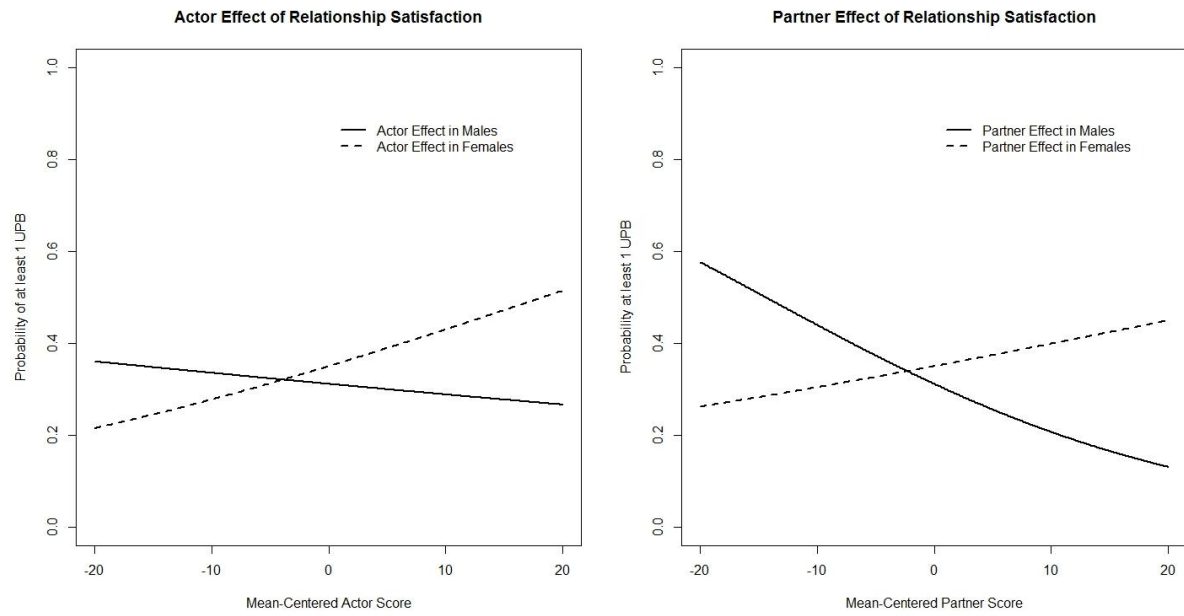


Figure 2

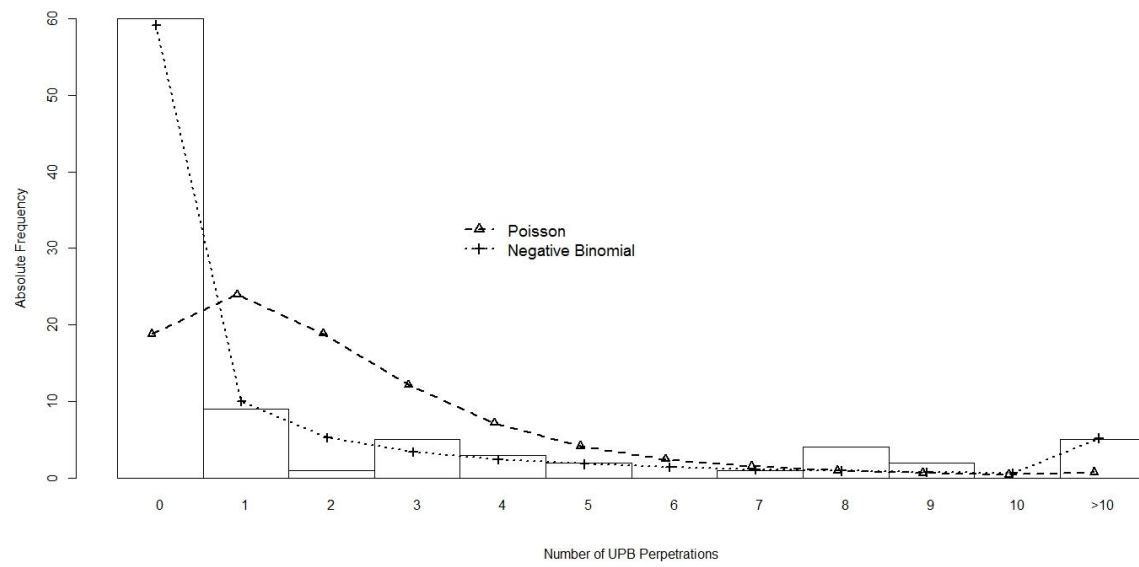


Figure 3

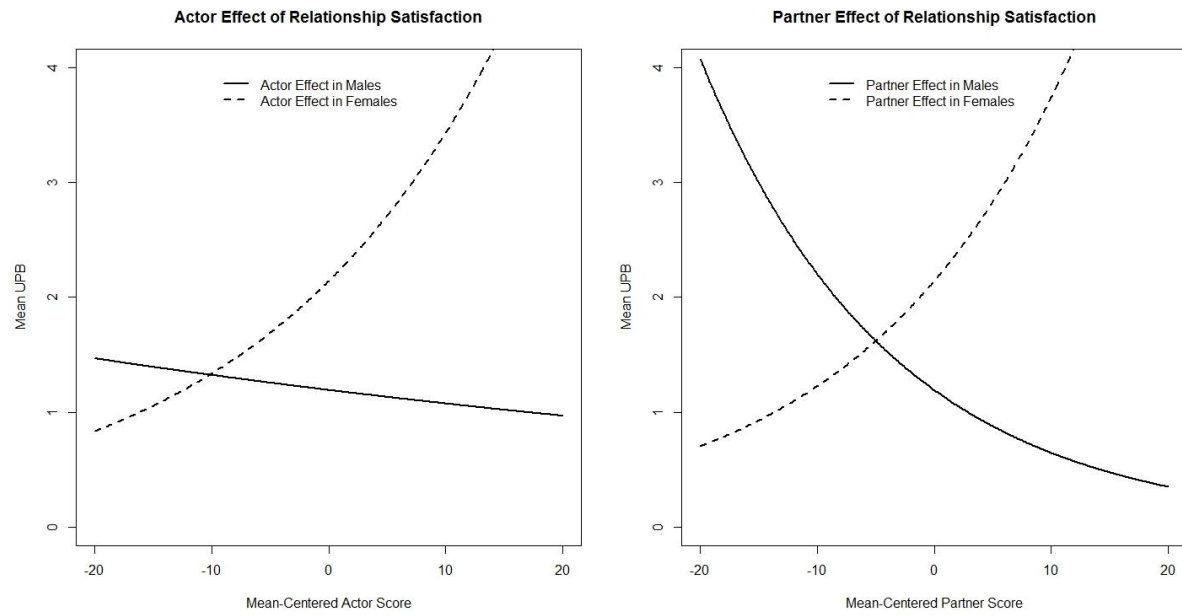


Figure 4