PEER EFFECTS AND MULTIPLE EQUILIBRIA IN THE RISKY BEHAVIOR OF FRIENDS

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Abstract—We study social interactions in the initiation of sex and other risky behaviors by best friend pairs in the Add Health panel. Focusing on friends with minimal experience at the baseline interview, we estimate bivariate ordered-choice models that include both peer effects and unobserved heterogeneity. We find significant peer effects in sexual initiation: the likelihood of initiating intercourse within a year increases by almost 5 percentage points (on an 11% base rate) if one's friend also initiates intercourse. Similar effects are present for smoking, marijuana use, and truancy. We find larger effects for females and important asymmetries in nonreciprocated friendships.

I. Introduction

MANY parents worry that their teenage children will imitate the bad behavior of their friends. Nevertheless, the actual magnitude of the peer effects in adolescent decision making is unclear. True social interaction effects are difficult to distinguish from unobserved background factors that are correlated across friends (Manski, 1993; Moffitt, 2001). Recent studies have tried to sidestep this problem by focusing on interactions within randomly assigned peer groups.[1] The peer effects observed in such settings, however, may not reflect the magnitude of the social interactions in naturally occurring friendships. Indeed, recent work by Carrell, Sacerdote, and West (2011) suggests that relatively small changes in the assignment process in a randomized design can lead to very different patterns of social interactions, depending on the friendship networks that are formed after the group is assigned.

In this paper, we use detailed panel data to directly measure the interaction effects between best friend pairs in the National Longitudinal Study of Adolescent Health (Add Health). Our main focus is on interactions in the decision to initiate sexual activity. Rather than rely on random or quasi-random variation in the characteristics of friends, we estimate simple structural models that incorporate social interaction effects and correlated unobservable determinants of their joint behavior.[2] We use a combination of exclusion restrictions and parametric assumptions on the distribution of unobserved heterogeneity to identify the relative contributions of peer effects and correlated heterogeneity. Our behavioral models imply a positive probability of multiple equilibria.[3] In such cases we assume that the observed outcomes are generated by a simple equilibrium selection rule (Bjorn & Vuong, 1984; Bajari, Hong, & Ryan, 2009).

Four features of the Add Health data set are central to our analysis. First, the study collected detailed information on networks of friends that can be used to identify relationships between sample members.[4] Second, the Add Health sample frame included a set of "saturated" high schools where all students were included in the survey. Since friends typically attend the same school, this design greatly increases the number of best friend pairs that can be followed over time. Third, the baseline and follow-up surveys include detailed questions on risky behaviors that provide the basis for our analysis. Finally, Add Health collected a rich set of individual characteristics, including family background variables and measures of physical development, that are relatively strong predictors of risky behavior.

We develop and estimate a series of bivariate ordered choice models for the behavior of friends that include both social interaction effects and unobserved heterogeneity across pairs. Our estimated models reveal quantitatively important social interaction effects in the sexual initiation of teenage friends. For example, the likelihood that one friend initiates intercourse in the year following the baseline interview is increased by about 5 percentage points (on a base rate of 11%) if the other also initiates intercourse,

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[1] For example, studies have analyzed quasi-experimental variation in neighborhoods (Oreopoulos, 2003; Jacob, 2004; Kling, Liebman, & Katz, 2007), classmates (Argys & Rees, 2008; De Giorgi, Pelizzari, & Redaelli, 2010), college roommates (Sacerdote, 2001; Zimmerman, 2003; Kremer & Lavy, 2008; Stinebrickner & Stinebrickner, 2006), and squadrons in the U.S. Air Force Academy (Carrell, Fullerton, & West, 2009). Though the results of these studies vary, several find very little evidence of peer effects, including Oreopoulos (2003), Sacerdote (2001), and Zimmerman (2003).

[2] A similar approach is taken by Huang (2010), who studies participation by family members in cell phone network service contracts. Krauth (2006, 2007) considers situations where only the choices of one member of a peer group and the average choice of the remaining members are observed and makes an assumption about the correlation between the unobserved determinants of friends' choices.

[3] The same issue arises in market entry games: see Bresnahan and Reiss (1990, 1991), Tamer (2003), and Ciliberto & Tamer (2009).

[4] See Smith and Christakis (2008) for a review of the literature on social networks and health, much of which has relied on Add Health. Other studies that have used the social network data in Add Health include Haynie (2001), Fryer and Torelli (2010), Bramoulle, Djebbari, and Fortin (2009), and Halliday and Kwak (2009).

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holding constant a wide range of controls. Overall, we estimate that about one-tenth of individuals make choices that are directly affected by their friend's choice.

We present a variety of checks to probe the robustness of these conclusions. As a falsification exercise, we construct pairs of "false friends" whose observed characteristics are closely matched and refit our models treating their background characteristics as unobserved. Reassuringly, estimates from these models show no peer interaction effects. To evaluate the importance of our parametric assumptions, we switch from our baseline bivariate ordered probit model to a bivariate ordered logit model with a flexible correlation parameter, using the copula function proposed by Ali, Mikhail, and Haq (1978).[5] Finally, we consider alternative assumptions on the effects of the friend-specific covariates, including models in which all the covariates of one friend are allowed to directly affect the choices of the other (models with "no exclusion restrictions"). Estimates of the social interaction effects and the degree of correlation between the unobserved determinants of the friends' choices are stable across the alternatives.

We go on to investigate the degree of heterogeneity in the strength of peer interaction effects. We find stronger peer effects for females.[6] We also find potentially important asymmetries in the interactions between friends, depending on the degree of reciprocity in their relationship. Finally, we fit similar models for peer interactions in cigarette smoking, marijuana use, and truancy and find generally similar patterns of interaction effects in these behaviors.

The next section of this paper lays out our econometric modeling framework and provides links to the related literatures. Section III discusses the Add Health data set and the construction of our analysis samples. Section IV presents our main estimation results, focusing on models for sexual initiation. We present a series of robustness checks in section V and address sample selection issues and models with asymmetric relationships between friends in section VI. We briefly summarize the results for other risky behaviors in section VII and present some concluding remarks in section VIII.

II. Modeling the Interactions of Friends

A. Bivariate Choice Models

Many observers have noted that adolescents tend to emulate the behavior of their friends and peers (Berndt, 1982; Akerlof, 1997). To formalize this idea, consider a pair of friends, each of whom can choose one of three levels of a risky behavior (y), indexed by {0,1,2}. We will think of $y = 0$ as representing abstinence, $y = 1$ as representing an intermediate level of participation (such as intimate touching in the case of sex), and $y = 2$ as a higher level of participation (such as intercourse). Let $u^i(y_i, y_{-i})$ represent the payoff to individual i when she chooses action $y_i \in \{0,1,2\}$ and her friend chooses action $y_{-i} \in \{0,1,2\}$. We assume that friends can observe each other's choices and choose simultaneously, so their decision problem can be represented as a complete-information simultaneous-move game with a 3×3 matrix of payoffs. In general, such games can have a single unique equilibrium, multiple equilibria, or no equilibrium in pure strategies.[7]

We simplify the payoff structure of the game by assuming that in the absence of social interaction effects, each friend's choice can be represented by a conventional ordered choice model (for example, an ordered probit or ordered logit). Specifically, we assume that for individual i, the difference in payoffs between sequential levels of intensity depends on the sum of a latent index of observed and unobserved factors, y_i^*, and one of two threshold functions, $c_1(y_{-i})$ or $c_2(y_{-i})$ that depend on the choice made by her friend:[8]

$$u^i(1, y_{-i}) - u^i(0, y_{-i}) = y_i^* - c_1(y_{-i}), \tag{1a}$$

$$u^i(2, y_{-i}) - u^i(1, y_{-i}) = y_i^* - c_2(y_{-i}), \quad \text{with } c_2(y_{-i}) \geq c_1(y_{-i}). \tag{1b}$$

Notice that if $c_1(y_{-i})$ and $c_2(y_{-i})$ are independent of y_{-i}, then i's choices are based on a simple partition of y_i^* with thresholds at c_1 and c_2:

$$\begin{aligned} y_i &= 0 \quad \text{if} \quad y_i^* \leq c_1, \\ y_i &= 1 \quad \text{if} \quad c_1 < y_i^* \leq c_2, \\ y_i &= 2 \quad \text{if} \quad y_i^* > c_2. \end{aligned}$$

Assuming that $y_i^* = X_i\beta + \varepsilon_i$, this leads to a standard ordered choice model where X_i represents a set of observed characteristics, β is a parameter vector, and ε_i is interpreted as a component of preferences that is known by the decision maker but unknown to outside analysts, and is distributed across the population according to some distribution function $F(\varepsilon_i)$.

Interaction effects in the thresholds allow the choice probabilities for friend 1 to depend on the actual choices of

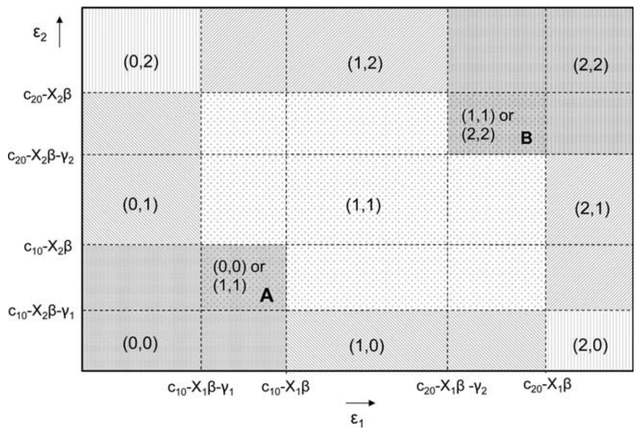
[5] The Ali et al. (1978) copula is a member of the class of Archimedean copulas (Nelsen, 2006) and allows positive, negative, or zero dependence between the two latent distributions. This copula generalizes the (highly restrictive) bivariate logit model proposed by Gumbel (1961).

[6] Others have emphasized gender differences in the magnitude of peer effects based on college roommates (Stinebrickner & Stinebrickner, 2006), classmates (Argys & Rees, 2008), and neighborhoods (Kling et al. 2007).

[7] Soetevent and Kooreman (2006) analyze equilibria among groups of friends of size n and show that the number of equilibria in the presence of social interaction effects grows exponentially in n. In light of this problem, we focus on the simplest possible case of $n = 2$.

[8] The assumption that the threshold functions are the same for the two friends seems natural when the two are reciprocated best friends. Later in the paper, we consider asymmetric friendship relationships and allow different threshold functions.

FIGURE 1.—PARTITION OF (ε_1, ε_2) FOR BIVARIATE ORDERED PROBIT



friend 2 and vice versa. The choices of the two friends can be represented by a bivariate ordered choice system:

$$y_i^* = X_i\beta + \varepsilon_i,$$
$$y_i = 0 \text{ if } y_i^* \leq c_1(y_{-i});\ y_i = 1 \text{ if } c_1(y_{-1}) < y_i^* \leq c_2(y_{-i});$$
$$y_i = 2 \text{ if } y_i^* > c_2(y_{-i}), \tag{2}$$

for i =1,2. Note that in general, the unobserved components of preferences of the two friends may be correlated, reflecting unobserved factors that determine their propensities to engage in a higher level of the behavior. For most of our analysis, we assume that (ε_1, ε_2) have a bivariate normal distribution with correlation ρ. As an alternative, we consider a correlated bivariate logistic distribution based on the copula function proposed by Ali et al. (1978).

To complete the model, we need to specify the threshold functions $c_1(y)$ and $c_2(y)$. As a baseline case, we assume that

$$c_1(y) = c_{10} - \gamma_1(y \geq 1), \tag{3a}$$

$$c_2(y) = c_{20} - \gamma_2(y = 2), \tag{3b}$$

where $c_{20} > c_{10,}\ \gamma_1 \geq 0$, $\gamma_2 \geq 0$, and $c_{20} - \gamma_2 > c_{10}$.[9] These equations imply that the social interaction effect on the threshold for a particular level of activity depends on whether the friend has selected the same or higher level of activity.[10] We consider more general models for $c_1(y)$ and $c_2(y)$ in section IV and find that the restrictions implied by equations (3a) and (3b) are consistent with the data.

Conditional on $X_1\beta$ and $X_2\beta$, equations (2) and (3) lead to a partition of the (ε_1, ε_2) space that maps into the nine possible outcomes for (y_1, y_2).[11] As shown in figure 1, there are two regions with multiple equilibria: region A, where (0,0) and (1,1) are both possible, and region B, where (1,1) and (2,2) are both possible. Notice that if the highest level of activity ($y_i = 2$) is treated as the main outcome of interest and the two lower levels are pooled, figure 1 collapses to the simpler partition associated with a bivariate discrete choice game analyzed by Soetevent and Kooreman (2006). Likewise if the two higher levels of activity are pooled, figure 1 collapses to a bivariate discrete choice model.[12]

In this paper, we estimate the model represented by equations (2) and (3) by maximum likelihood, adding a simple equilibrium selection model to determine the observed outcome when (ε_1, ε_2) fall in a region of multiple equilibria. Specifically, following Bjorn and Vuong (1984), we assume that when (ε_1, ε_2) fall in region A or B, we observe the pair choosing the higher choice with probability one-half and the lower choice with probability one-half. As a robustness check, we consider simple variants in which both friends always select either the higher level or the lower level in any region of multiple equilibria.[13]

In an earlier version of this paper (Card & Giuliano, 2011), we also considered the partial likelihood approach suggested by Bresnahan and Reiss (1990, 1991), which remains agnostic about equilibrium selection. This approach uses conventional likelihood expressions for the six values of (y_1, y_2) that can be mapped back to unique regions of (ε_1, ε_2) and assigns the remaining probability to the set of remaining values (i.e., (y_1, y_2) ∊ {(0,0), (1,1), (2,2)}. Unfortunately, given our limited sample sizes, this approach does not yield informative estimates, so we focus here on models with a simple selection mechanism.[14]

B. *Identification*

An immediate concern that arises in interpreting results from the model based on equations (2) and (3) is identification. Positive social interaction effects generate a correlation across the observed choices of best friends that is similar to the pattern caused by a positive correlation between ε_1 and ε_2. Two features of the model allow separate identification of the competing explanations. The first is exclusion restrictions. Specifically, if $X_1 \neq X_2$, then (loosely speaking)

[9] Note that we could have alternatively parameterized the threshold functions as $c_1(y) = c_{11} + \gamma_1$ $(y = 0)$ and $c_2(y) = c_{22} + \gamma_2$ $(y \leq 1)$, which would imply different values for the constant terms but the same values for γ_1 and γ_2.

[10] In particular, the threshold between the lower and intermediate level $c_1(y)$ is the same whether y = 1 or y = 2, while the threshold between the intermediate and high level $c_2(y)$ depends on only whether y = 2.

[11] The ordered structure of preferences implies that there is always at least one equilibrium in pure strategies for any possible value of the Xs and (ε_1, ε_2). We do not consider mixed strategy equilibria.

[12] One justification for the restrictions in equations (3a) and (3b) is that these are necessary and sufficient to ensure that the ordered model can be collapsed to a dichotomous model by pooling either the two lower activity levels or the two higher activity levels. The more general threshold functions considered below lead to a model that cannot be estimated consistently after pooling.

[13] A more flexible approach is to posit a parametric model for the equilibrium selection probability that depends on the characteristics of the friends, as suggested by Bajari et al. (2009). As we discuss in more detail below, our estimated models imply that the probability of multiple equilibria is quite low (about 0.5%), and our attempts to estimate parametric selection models suggest that the parameters are very poorly identified.

[14] In Card and Giuliano (2011), we also implement a version of the quasi-likelihood approach that Tamer (2003) suggested, which uses estimates of the probabilities for two of the three outcomes that can arise from regions of multiplicity ($p((y_1, y_2) = (1,1) \mid X_1, X_2)$ and $p((y_1, y_2) = (2,2) \mid X_1, X_2)$.

the distinct elements of X_1 serve as instruments for y_1 in the model for y_2^*, while the distinct elements of X_2 serve as instruments for y_2 in the model for y_1^*. For our main models, we rely on this source of identification by assuming that an individual's observed characteristics have no effect on her friend's choices (that X_1 and X_2 are distinct), though we relax this assumption below. A second feature is the combination of a simple parametric distribution for (ε_1, ε_2) and the functional form of equations (2) and (3), which assumes that the friend's choices exert an additive effect on the latent index of behavior. As Heckman (1978, 1981) and Hyslop (1999) discuss in detail, in a parametrically specified dynamic discrete choice model, the contributions of state dependence and unobserved heterogeneity to the observed patterns of serial correlation in the choice outcome are separately identified. The same intuition applies to our bivariate discrete choice model.

Nevertheless, it is an empirical question whether the models can reliably distinguish between unobserved heterogeneity and social interaction effects in a realistically sized sample. To provide some guidance, we conducted a Monte Carlo study in which we generated data on the sexual behavior of best friend pairs from one of three alternative data-generating processes (DGPs): (a) a DGP with social interaction effects but no correlation in the unobserved error components ($\gamma_1 > 0$, $\gamma_2 > 0$, ε_1 and ε_2 uncorrelated normal variates), (b) a DGP with correlated unobserved heterogeneity but no social interaction effects ($\gamma_1 = 0$, $\gamma_2 = 0$, ε_1 and ε_2 correlated normal variates with correlation ρ), and (c) a DGP with both social interaction effects and correlated heterogeneity. We then fit different versions of our model by maximum likelihood and examined the sampling distributions of the estimated social interaction and error correlation parameters.

Details of the simulation models and the resulting distributions of estimation errors are summarized in the appendix. We chose a sample size for each simulated data set ($n = 1{,}000$) to roughly match the size of our Add Health sample. We calibrated the constants and the parameters ρ, γ_1, and γ_2 in each of the three DGPs to generate a 3×3 cross-table of outcomes for the friend pairs that closely matches the actual cross-tabulation of sexual initiation behavior in our sample. For the model with social interactions but no correlation in the errors, this led us to choose values of $\gamma_1 = 0.20$ and $\gamma_2 = 0.25$. For the model with correlated heterogeneity but no social interactions, this led us to choose $\rho = 0.25$. Finally, for the model with both, we selected $\gamma_1 = 0.10$, $\gamma_2 = 0.15$, and $\rho = 0.15$. We also compared two designs for the observed covariates. The first design has a pair of normally distributed covariates, x_1 and x_2, with a correlation equal to that of the covariate indexes observed in our sample of best friend pairs, and a coefficient β that yields a pseudo-R^2 for the ordered outcome that roughly matches the pseudo-R^2 from an ordered probit for the initiation of sexual behavior in our sample (around 0.08). The second design has the same observed covariates but with $\beta = 0$. In this design, identification is based entirely on the (correct) parametric assumptions about the error distribution and the model for the observed y's.

The simulation results suggest that if the true data were generated by a model with normal errors, we would be able to draw useful inferences about the relative contributions of unobserved heterogeneity and social interactions from samples of 1,000 friends, even with relatively weak covariates. In particular, if the true model includes only unobserved heterogeneity and we fit a model that allows both social interaction effects and correlated errors, the estimates of the social interaction parameters would be centered relatively tightly around 0. (For the first covariate design with $\beta > 0$, the standard deviations of the estimates of γ_1 and γ_2 across replications are both about 0.04; for the second design, with $\beta = 0$, the standard deviations are about 20% larger). Similarly, if the true model includes both unobserved heterogeneity and social interaction effects, even with samples of size 1,000, the estimates of the interaction parameters would be relatively tightly centered around their true values.

While reassuring, these results have to be interpreted carefully because we are assuming that the true functional form of the model is known and that the errors have a bivariate normal distribution. In section V, we present two additional robustness checks that use our actual data set to address these limitations. First, we construct pairs of false friends whose behaviors are correlated but who (by construction) are unaffected by social interactions and check whether the estimated models lead to correct inferences. Second, we refit our models using an alternative correlated bivariate logistic functional form.

III. Data and Sample Construction

A. *The Add Health Data Set*

We use data from waves 1 and 2 of the National Longitudinal Study of Adolescent Health (Add Health), which collected longitudinal information for a sample of U.S. adolescents who were in seventh through twelfth grades in the 1994–95 school year (Harris et al., 2009), including unique information on the friendship networks of sample members. The sample frame for the study included a random sample of eighty high schools, plus the largest middle school that fed into each high school. In wave 1, an in-school questionnaire was administered to all those who were present on the day of the survey ($n > 90{,}000$). A subsample of enrollees was then selected to be interviewed at home: 20,745 in-home interviews were completed.[15] One year later, a second wave of in-home interviews was administered to the same group, yielding a panel of 14,736 students with data

[15] Students were eligible for in-home interviews even if they did not complete the in-school questionnaire. Their parents completed a separate in-home interview.

from the wave 1 and wave 2 in-home surveys.[16] Importantly, the Add Health sample design included sixteen schools in which all students were eligible for the in-home interview. Given that most friendships occur among students who attend the same school, these "saturated" sample schools provide many of the best friend pairs who are included in both waves of in-home interviews.

B. *Construction of Friend Pairs*

Add Health collected information on friends from both the in-school and in-home interviews in wave 1. The in-school questionnaires asked respondents to list up to five friends of each gender (with best friends listed first). The in-home interview for students in saturated schools had a similar question, while the interview for students at nonsaturated schools asked them to name a best friend of each gender. We use this information for the subset of adolescents who completed both the wave 1 and wave 2 in-home interviews to construct pairs of best friends who can be followed over time.[17]

We began by matching respondents from the longitudinal subsample who nominated each other as best friends in the wave 1 in-home interview. Next, we matched all remaining respondents to their best friend nominees from the in-home interview whenever those nominations were reciprocated by the nominees on the in-school questionnaire.[18] Then we matched all remaining respondents who nominated each other as best friends on the in-school questionnaire. These three steps resulted in 667 "reciprocated" best friend pairs. In a fourth step, all unmatched respondents were paired with their in-home or in-school best-friend nominee, if that person was in the longitudinal subsample and still unmatched, with priority given to in-home nominees. This process yielded an additional 1,201 nonreciprocated friend pairs.[19] In all, we have 1,868 friend pairs who were interviewed in both the wave 1 and wave 2 surveys. We note that the relatively low fraction of respondents who can be matched to a best friend is mainly due to the fact that many of the listed best friends were not included in the longitudinal subsample.

C. *Outcomes and Estimation Samples*

Our main outcome of interest is a measure of sexual initiation between the first and second waves of the Add Health data. For this analysis, we use a subsample of 738 friend-pairs with minimal sexual experience as of the wave 1 interview.[20] (In section VI, we address potential concerns associated with this sample selection rule.) We use wave 2 data to classify sexual experience one year later into three categories: minimal, intermediate, and high. We assign the intermediate level of activity to respondents who reported at least one opposite-sex relationship as of wave 2 that involved "touching each others' genitals" but not having intercourse. We assign the high level of activity to those who reported having had intercourse.

We use a similar procedure to construct ordered measures of initiation for three other risky behaviors: cigarette smoking, marijuana use, and truancy.[21] We define intermediate-level smokers as those who had tried cigarettes as of wave 2 but were not regular smokers and high-intensity smokers as those who smoked regularly—that is, at least one cigarette every day for thirty days. Similarly, we define intermediate marijuana use as having tried marijuana as of wave 2 and high-level use as having used marijuana one or more times in past thirty days. For truancy, we define the intermediate-level behavior as having skipped school only once during the wave 2 school year (1995–96), and the high-level behavior as having skipped more than once. Our estimation samples for analyzing these behaviors consist of 738 friend pairs who had never smoked an entire cigarette as of wave 1, 1,076 pairs who had never tried marijuana, and 964 pairs who had not skipped school during the wave 1 school year (1994–95).

D. *Individual and Household Characteristics*

In our empirical models, we control for the respondents' age, race, and gender, as well as the following individual and family characteristics:

- *Physical development index,* based on wave 1 responses to three gender-specific questions on physical development. We convert the answer to each question to a z-score and take the average.
- *Attitude toward risk,* based on strength of agreement with the statement, "You like to take risks."[22] This is reported on a scale from 1 (strongly disagree) to 5 (strongly agree).
- *Future orientation,* based on agreement with the statement: "You live your life without much thought for the

[16] The main loss of sample between wave 1 and wave 2 arose from the graduation of twelfth-grade students. Graduates were not reinterviewed unless they had younger siblings in the school.

[17] We include nonresponders to the in-school questionnaire, who represent about 20% of our sample.

[18] We give primacy to the in-home interview because our other baseline variables are measured at the time of this interview and because 20% of respondents did not complete the in-school questionnaire.

[19] Data for the subset of respondents who provided multiple friendship nominations (those who completed the in-school questionnaire or were in a saturated school, or both) suggest that just over half of those who received but did not reciprocate a best friend nomination listed the nominator as one of their five best friends.

[20] In both waves 1 and 2 of the in-home interview, sample members were asked if they had ever had sexual intercourse. They were also asked to list all romantic and sexual relationships within the past eighteen months and to check off a list of sexual activities that had occurred in each relationship. The in-home interviews were done using a laptop computer with confidential audio-CASI sections for questions about illegal and risky behaviors.

[21] Initially we also examined alcohol use but found little evidence of correlation in the initiation of alcohol use among friends. Hence we do not model the initiation of alcohol use, though we use wave 1 information on alcohol as a control variable in some of our specifications.

[22] This question and the "future orientation" question were asked only in wave 2.

TABLE 1.—DESCRIPTIVE STATISTICS FOR VARIOUS SAMPLES

	Full Wave 1 and 2 Sample	Same-Sex Best Friend Pairs	Best Friends with No Touching or Intercourse at Wave 1
	(1)	(2)	(3)
Individual and family characteristics			
Age (in years, as of wave 1)	15.80	15.79	15.14
Male	0.49	0.45	0.43
Black race	0.22	0.19	0.14
Other nonwhite race	0.15	0.17	0.17
GPA (wave 1, 1–4 scale)	2.73	2.81	3.01
Physical development index	0.13	0.16	−0.04
Attitude toward risk (1–5 scale)	3.54	3.55	3.47
Future orientation (1–5 scale)	3.58	3.60	3.65
Time preference (1–5 scale)	1.58	1.58	1.53
Smokers in household (yes/no)	0.42	0.40	0.33
Two-parent household (yes/no)	0.68	0.71	0.77
Frequency that parents attend church (0–3 scale)	1.76	1.82	1.89
Parents not religious (yes/no)	0.19	0.17	0.15
Parental church attendance missing	0.12	0.12	0.11
At least one parent finished high school	0.88	0.88	0.90
At least one parent finished college	0.37	0.38	0.43
Parental education missing	0.05	0.04	0.03
Risky behaviors as of wave 1			
Intimate touching	0.43	0.40	0.00
Had intercourse	0.35	0.31	0.00
Tried cigarette smoking	0.41	0.39	0.24
Smoked cigarettes regularly	0.18	0.15	0.05
Tried marijuana	0.26	0.25	0.09
Used marijuana regularly	0.14	0.13	0.04
Skipped school one or more days	0.27	0.26	0.13
Skipped school two or more days	0.20	0.18	0.08
Drank alcohol without adult presence	0.38	0.38	0.21
Drank alcohol regularly	0.16	0.15	0.05
Sexual Experiences as of wave 2			
Intimate touching with opposite sex	0.531	0.517	0.222
Had intercourse	0.450	0.429	0.138
Number of observations	13,836	3,368	1,476

See the text for a description of the algorithm for identifying best friend (BF) pairs.

future." This is reported on a scale from 1 (strongly agree) to 5 (strongly disagree).

- *Time preference,* based on responses to two questions about the likelihood of contacting HIV/AIDS or being killed by age 21. The responses are scaled from 1 (almost no chance) to 5 (almost certain); we average the two responses.
- *Smokers in household,* a dummy set to 1 if the parent interview in wave 1 indicated that there were smokers in the household or if the interviewer reported evidence of smoking in the household.
- *Two-parent household,* a dummy for the presence of two parents as of wave 1.
- *Frequency parents attend church,* based on the wave 1 parent interview, with four values from 0 (never) to 3 (once a week or more). Missing values are set to 0, and we include a dummy for these cases. We also assign a separate indicator for *parents not religious* if the parent reported either having no religion or never going to church.
- *Parental education measures,* based on wave 1 reports of parental education. We classify families with two indicators: (a) at least one parent has completed high school and (b) at least one parent has completed college. Missing values are set to 0, and we include a dummy for missing data.

In our "extended" specifications we also control for wave 1 GPA, defined as the average of the respondent's self-reported grades in English and math, and for baseline levels of experience in the other risky behaviors (smoking, marijuana use, truancy, and alcohol use in the models for sexual initiation).

E. Sample Statistics

Table 1 presents summary statistics for the variables in our analysis. Column 1 shows characteristics for all Add Health respondents who completed the wave 1 and wave 2 interviews. Column 2 includes only individuals assigned to a best friend pair, while column 3 is further restricted to best friend pairs with minimal sexual experience at wave 1. Looking first at the first section of table 1, the individual and family background characteristics of respondents who can be combined into best friend pairs (column 2) are not too different from the overall Add Health sample (column 1), though the matched friends include more girls than boys and are more likely to come from religious and two-parent

TABLE 2.—CORRELATIONS IN COVARIATES BETWEEN FRIEND PAIRS

	All Same-Sex Best Friend Pairs		Best Friend Pairs with No Touching or Intercourse at Wave 1	
	Raw	Adjusted	Raw	Adjusted
	(1)	(2)	(3)	(4)
Individual and family characteristics:				
Age (in years, as of wave 1)	0.85	–	0.88	–
Black race	0.86	–	0.84	–
GPA (wave 1, 1–4 scale)	0.34	0.31	0.40	0.38
Physical development index	0.27	0.14	0.27	0.15
Attitude toward risk (1–5 scale)	0.09	0.07	0.08	0.06
Future orientation (1–5 scale)	0.14	0.13	0.15	0.14
Time preference (1–5 scale)	0.04	0.03	0.05	0.05
Smokers in household (yes/no)	0.17	0.16	0.17	0.14
Two-parent household (yes/no)	0.16	0.11	0.15	0.11
Frequency that parents attend church (0–3 scale)	0.28	0.24	0.32	0.31
Parents not religious (0–1)	0.18	0.24	0.17	
At least one parent finished high school	0.34	0.33	0.38	0.36
At least one parent finished college	0.31	0.31	0.27	0.27
Risky behaviors as of wave 1				
Intimate touching	0.33	0.22	–	–
Had intercourse	0.36	0.26	–	–
Tried cigarette smoking	0.29	0.24	0.25	0.24
Smoked cigarettes regularly	0.34	0.31	0.13	0.12
Tried marijuana	0.41	0.37	0.37	0.36
Used marijuana regularly	0.25	0.23	0.18	0.17
Skipped school one or more days	0.28	0.15	0.23	0.20
Skipped school two or more days	0.28	0.18	0.23	0.19
Drank alcohol without adult presence	0.29	0.21	0.26	0.17
Drank alcohol regularly	0.21	0.21	0.14	0.13
Number of friend pairs	1,684	1,684	738	738

Columns one and three show simple correlation coefficients between characteristics of best friends in each pair. Columns two and four show partial correlation coefficients that control for the gender, age, and race of both friends.

families. Students in the subsamples with limited sexual experience (column 3) are younger, more likely to be female, and have higher grades and slightly better-educated parents.

The second section of table 1 shows the rates of participation in various risky behaviors as of wave 1. About 40% of sample respondents report intimate touching and 35% report having had intercourse. These rates are a little lower for the respondents who can be matched to friend pairs and (by definition) are 0 for the subsample with minimal sexual experience as of wave 1. Incidence rates for the other risky behaviors are also in the 20% to 40% range but are lower for the subsamples with limited sexual experience.

Finally, the last section of the table reports levels of sexual experience at wave 2. Over the one-year interval between the waves, the overall fraction of Add Health respondents who report having had intimate contact or intercourse increases by 10 percentage points. Among those with minimal sexual experience as of wave 1 (column 3), the rates increase from 0 to 22% for intimate contact and from 0 to 14% for intercourse.

Table A2 shows the initiation rates for the other risky behaviors for the subsamples with minimal experience in the corresponding behaviors as of wave 1. These rates are lower than the initiation rate for sex, especially at the high-intensity level. Among friend pairs who had not smoked a cigarette as of wave 1, for example, the rate of transition to regular smoking is only 3%. For marijuana use, the initiation rates are 10% for experimental use and 6% for regular use, and for truancy, they are 16% for skipping one day and 8% for skipping more than one day.

Best friendships among adolescents are highly assortive by age, race, and other characteristics. This is shown in table 2 where we report the within-pair correlations for all best friends and for those with minimal sexual experience at wave 1. Ninety percent of best friends are within a year of age, and 86% of the time they are of the same race (defined as white, black, or other). The within-pair correlations of other characteristics are substantially lower, typically in the range of 0.2 to 0.3. Some of the correlation in characteristics like physical development is due to the strong assortiveness of friendships by age, race, and gender. When we adjust for these three characteristics (columns 2 and 4 of table 2), the within-pair correlations are 10% to 50% lower. Interestingly, the within-pair correlations are not too different for pairs with minimal sexual experience, suggesting that our sample restriction to inexperienced pairs does not substantially change the degree of assortiveness of the friendships.

IV. Main Estimation Results

A. *Bivariate Ordered Probit Models for Initiation of Sexual Activity*

Table 3 presents a series of estimated bivariate ordered probit models for the initiation of sexual activity among

TABLE 3.—SUMMARY OF BIVARIATE ORDERED PROBIT MODELS FOR SEXUAL ACTIVITY BY FRIEND PAIRS

	Baseline Covariates				Expanded Set of Covariates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Include wave 1 behaviors and GPA?	No	No	No	No	Yes	Yes	Yes	Yes
Error correlation (ρ)	–	0.24	–	0.06	–	0.18	–	0.02
		(0.06)		(0.09)		(0.07)		(0.10)
Social interaction effect: Intermediate level of activity (γ_1)	–	–	0.20	0.16	–	–	0.16	0.15
			(0.05)	(0.08)			(0.06)	(0.08)
Social interaction effect: High level of activity (γ_2)	–	–	0.27	0.22	–	–	0.23	0.21
			(0.06)	(0.09)			(0.06)	(0.09)
Log likelihood	−949.86	−943.75	−941.25	−941.12	−894.06	−890.85	−888.65	−888.63
Goodness of fit (9 cells)	22.17	4.61	1.75	0.94	12.01	4.28	0.57	0.47

Standard errors, clustered by school, in parentheses. See the text for model descriptions. Sample includes 738 friend pairs with minimal sexual experience at wave 1. The dependent variable is an ordered variable indicating intimate touching, intercourse, or neither. Models in columns 1–4 include two constants and sixteen other person-specific controls. Models in columns 5–8 include these controls plus wave 1 GPA and eight additional dummies indicating levels of experience in cigarette smoking, marijuana use, truancy, and alcohol use as of wave 1. Coefficients for covariates are reported in table A3.

best friend pairs. To keep the tables readable, we report only the estimates of the error correlation ρ, the social interaction effects γ_1 and γ_2, the maximized log likelihood, and a measure of the goodness of fit of the model, which is based on the deviations between the predicted and actual number of pairs with each of the nine possible outcomes. (Coefficients and standard errors for the covariates are reported in table A3.) We present four specifications: a benchmark model with neither correlated heterogeneity nor social interaction effects ($\rho = \gamma_2 = \gamma_1 = 0$) in columns 1 and 5, a model with only correlated heterogeneity ($\gamma_2 = \gamma_1 = 0$) in columns 2 and 6, a model with only social interaction effects ($\rho = 0$) in columns 3 and 7, and a general model in columns 4 and 8. The specifications in columns 1 to 4 include our baseline set of individual and family characteristics, while the models in columns 5 to 8 include the baseline covariates plus wave 1 GPA and eight dummy variables indicating experience in cigarette smoking, marijuana use, truancy, and drinking alcohol as of wave 1.

Looking first at the benchmark models with no correlated heterogeneity or social interaction effects, we see that the goodness-of-fit summary statistics in the bottom row of the table suggest that these models are unable to adequately fit the degree of correlation between friends in their ordered outcomes.[23] Allowing either a correlation in the unobserved errors (columns 2 and 6) or social interaction effects (columns 3 and 7) leads to a substantial improvement in fit. Further improvements from the combined models, which include both factors (columns 4 and 8), are relatively small. As expected, the models with only correlated heterogeneity yield positive estimates of ρ, while the models with only social interactions show positive peer effects between the friends.

Most interesting are the models that allow both correlated heterogeneity and social interactions (columns 4 and 8). In these models, the estimates of ρ are small and statistically insignificant, while the estimates of the social interaction effects γ_1 and γ_2 are relatively large in magnitude and significant. Perhaps surprisingly, the general models suggest that after controlling for the observed X's, nearly all of the correlation in the outcomes of best friends is attributable to social interaction effects.

[23] For comparison purposes, the simple chi-squared statistic for the outcomes of the pairs across the nine possible cells with no adjustment for the effects of the covariates is 28.60. The 5% critical value for a chi-square with 8 degrees of freedom is 15.5.

TABLE 4.—ESTIMATED CONDITIONAL PROBABILITIES FOR SEXUAL ACTIVITY

	Predicted Probability (%)	Peer Effect (change in %)
Initiates high level activity when friend does not	11.4	4.9
Initiates high level activity when friend does	16.3	
Initiates intermediate activity when friend does not	19.7	4.7
Initiates intermediate activity when friend does	24.4	

The first column shows conditional probabilities of intiating a behavior, taking the friend's behavior as given, for an individual with average characteristics. Probabilities are calculated using estimated parameters from the baseline model shown in table 3, column 4.

The magnitudes of the implied peer effects are illustrated in table 4. Here we use the coefficients from the specification in column 4 of table 3 to simulate how the average probability of initiating each level of sexual activity changes when the friend's behavior switches from a lower level of activity to the same level of activity or higher. The interaction effects are sizable and suggest that peer behavior exerts an important influence on the sexual initiation behavior of teenagers. Specifically, the likelihood of initiating intercourse increases by 4.9 percentage points (on a base rate of 11%) if one's friend also initiates intercourse and the likelihood of initiating intimate contact is increased by 4.7 percentage points (on a base rate of 20%) if one's friend does the same.

Some context for the size of these effects is provided by comparing them to the effects of the individual and family background characteristics in our models (these are reported in table A3). Indicators for living in a single-parent household (versus a two-parent household) or having at least one parent who finished high school (versus neither) have coefficients that are comparable in magnitude to the estimates of γ_1 and γ_2. Other factors that increase the likelihood of initiating sexual activity include age, black race, physical development, and self-reported attitude toward risk. (In contrast, measures of future orientation and time preference do not have much effect). Estimates from the expanded specifica-

TABLE 5.—ESTIMATED PROBABILITY THAT CHOICE OF SEXUAL ACTIVITY IS INFLUENCED BY FRIEND'S BEHAVIOR, INTENSITY LEVEL, AND TYPE OF INFLUENCE

		Own Decision Is Influenced by Friend's Behavior				
		Unique equilibrium: Friend's Influence Is:		Multiple Equilibria: mutual Influence is:		
Decision Outcome:	Not Influenced by friend	Moderating	Intensifying	Moderating	Intensifying	Total
Does not initiate sexual activity	0.744	0.033	–	0.001	–	0.777
Initiates intermediate–level activity	0.033	0.040	0.010	0.001	0.001	0.086
Initiates high-level activity	0.129	–	0.007	–	0.001	0.137
Subtotal	–	0.072	0.018	0.003	0.003	–
Sum of probabilities	0.906	0.090		0.005		1.000

Estimates based on simulations of model shown in column 4 of table 3.

tions in columns 5 to 8 suggest that experience with alcohol use by wave 1 is a strong predictor of the likelihood of beginning intercourse. The average probability of initiating intercourse over the next year is about 11 percentage points higher for respondents who had consumed alcohol without adult supervision at wave 1 than for those who had not—an effect about twice as large as the social interaction effects.

Another way to interpret the estimates of the social interaction effects is to ask how often individuals are directly influenced by their friends' decisions. Note that equations (2) and (3) imply that individual i's decision depends directly on the friend's behavior whenever

$$c_{20} - X_i\beta - \gamma_2 < \varepsilon_i < c_{20} - X_i\beta \text{ (in which case } y_i = 2 \text{ if } y_{-i} = 2 \text{ and 1 otherwise).}$$

or

$$c_{10} - X_i\beta - \gamma_1 < \varepsilon_i < c_{10} - X_i\beta \text{ (in which case } y_i = 1 \text{ if } y_{-i} \geq 1 \text{ and 0 otherwise).}$$

The average probabilities of these two conditions occurring in our sample are 4.7% and 4.9%, respectively, precisely the average peer effect estimates shown in table 4.[24] Overall, then, just under 10% of individuals' choices are directly influenced by their friends' choices.

A more detailed analysis is shown in table 5. For each level of sexual activity, we report the probabilities of engaging in the behavior for cases where the individual is not influenced by her friend, for cases where she is influenced unilaterally by her friend (her friend is not affected by her choice but she is in a region of influence), and for cases of bidirectional influence (both friends are in the region of influence and there are therefore multiple equilibria). We also distinguish between cases where the friend's choice has an intensifying influence on an individual's behavior (for example, when one chooses to initiate a higher level of intensity because her friend does) and cases where the friend has a moderating influence (for example, one stays at the lower level of intensity because her friend also does).

[24] For example, note that the effect of a change in the friend's behavior on the probability of $y_i = 2$ is based on the comparison of $P(\varepsilon_i > c_{20} - X_i\beta)$ versus $P(\varepsilon_i > c_{20} - X_i\beta - \gamma_2)$.

On average, when peer influence occurs, one friend is either highly unlikely or highly likely to initiate sex, and therefore exerts a unidirectional influence on her friend. Less than 1% of the population falls in the regions of multiple equilibria (regions A or B in figure 1) where the influence is bidirectional. Further, because the incidence of sexual initiation is relatively low in our sample, most of the influence of friends is moderating. Only in about 20% of cases is a friend led to choose a higher level of intensity because of her best friend's choice.

B. *Alternative Assumptions on Equilibrium Selection*

So far we have assumed that in regions of multiple equilibria, one of the two possible equilibria is selected at random. As shown in table 5, the estimated probability of falling in a region of multiple equilibria is very small, suggesting that the equilibrium selection assumption is unlikely to be important in driving our estimates. Estimates from models that make alternative assumptions about the equilibrium selection confirm the robustness of our results. In particular, we have estimated models similar to those in table 3, except that in cases of multiple equilibria, we assume both friends select either the higher choice or the lower choice. These "extreme" selection rules yield estimated peer effects, likelihoods, and goodness-of-fit statistics that are very similar to the 50-50 split baseline. Indeed, the peer effect coefficients differ by no more than 0.01 across models.[25]

C. *More Complex Models of Social Interactions*

The models estimated in table 3 assume that the threshold for a particular level of activity is affected by the same amount if the friend engages in that level of activity or a higher level. Under that assumption, there are only two

[25] More complete estimation results from these alternative models are reported in table 6 of Card and Giuliano (2011). There, we also report estimates from models using a partial likelihood approach that distinguishes seven outcome sets. Estimates from this approach are very imprecise, suggesting that the partial likelihood approaches ignore too much information for us to learn much about the relative magnitudes of γ_1 and γ_2 versus ρ in our (relatively small) sample.

TABLE 6.—SUMMARY OF GENERALIZED BIVARIATE ORDERED PROBIT MODELS FOR SEXUAL ACTIVITY BY FRIEND PAIRS

	Restricted Model		Unrestricted Model	
	(1)	(2)	(3)	(4)
Include wave 1 Behaviors?	No	Yes	No	Yes
Error correlation (ρ)	–	–	–	–
Social interaction effect				
Effect of intermediate level of activity by friend on decision to engage in intermediate-level activity (γ_{11})	0.20	0.16	0.23	0.18
	(0.05)	(0.06)	(0.06)	(0.06)
Effect of high level of activity by friend on decision to engage in intermediate-level activity (γ_{12})	0.20	0.16	0.23	0.18
	(0.05)	(0.06)	(0.06)	(0.06)
Effect of intermediate level of activity by friend on decision to engage in high-level activity (γ_{21})	–	–	0.11	0.06
			(0.08)	(0.08)
Effect of high level of activity by friend on decision to engage in high-level activity (γ_{22})	0.27	0.23	0.20	0.19
	(0.06)	(0.06)	(0.07)	(0.08)
Log likelihood	−941.25	−888.65	−940.57	−888.51
Goodness of fit (9 cells)	1.75	0.57	0.45	0.35

Standard errors, clustered by school, in parentheses. See the text for model descriptions. The sample includes 738 friend pairs who had not engaged in intercourse or intimate contact by wave 1. The dependent variable is an ordered variable indicating intimate touching, intercourse, or neither. The models in columns 1 and 3 include two constants and sixteen other person-specific controls. The models in columns 2 and 4 include sixteen same controls plus wave 1 GPA and eight additional dummies indicating level of experience in cigarette smoking, marijuana use, truancy, and alcohol use as of wave 1.

interaction effects, represented by γ_1 and γ_2. In this section, we consider a more general model that allows up to four possible interaction effects. Specifically, we replace equations (3a) and (3b) with

$$c_1(y) = c_{10} - \gamma_{11}(y = 1) - \gamma_{12}(y = 2), \tag{4a}$$

$$c_2(y) = c_{20} - \gamma_{21}(y = 1) - \gamma_{22}(y = 2). \tag{4b}$$

These equations allow the threshold for a particular level of activity to vary depending on whether the friend chooses the low, medium, or high level of activity. Our baseline model is a special case of this more general model with $\gamma_{11} = \gamma_{12}$ and $\gamma_{21} = 0$.

Assuming that $0 \leq \gamma_{j1} \leq \gamma_{j2}$ and $c_{10} \leq c_{20} - \gamma_{22}$, the generalized model has four regions with multiple equilibria: two that are similar to the regions in figure 1, a third region in which either (0,1) or (1,2) can occur, and a fourth where (1,0) or (2,1) can occur. We estimate the generalized model assuming that these conditions are satisfied and assigning equal probabilities to the two possible equilibria in any region of multiplicity. Given the findings in table 3, we also simplify the models by assuming that the error terms are uncorrelated ($\rho = 0$).

The results are summarized in table 6. For reference, the first two columns of the table reproduce the social interaction effects from our baseline specifications (the models reported in columns 3 and 7 of table 3). Estimates from the generalized specifications shown in columns 3 and 4 are relatively close to the baseline estimates, supporting the restrictions in equations (3a) and (3b). In particular in both columns 3 and 4, we estimate that $\gamma_{11} = \gamma_{12}$, implying that the threshold for the intermediate level of activity is shifted by the same amount when the friend chooses either the intermediate or higher level of activity.[26] The estimates of γ_{21} are also relatively small and insignificantly different from 0, implying that the threshold for the high level of activity is not significantly affected when the friend engages in the intermediate level of activity. We conclude that the simpler specification of effects assumed in equations (3a) and (3b) is adequate to describe the peer interactions in our data.

[26] Our parameterization restricts the difference $\gamma_{11} - \gamma_{12}$ to be strictly positive, and the parameter estimate for this difference is near the boundary of the allowable space.

V. Robustness Tests

A. *Models That Assume a Fixed Value for Rho*

In the following sections, we perform a series of checks on our model's ability to distinguish social interaction effects from correlation in the unobserved determinants of behavior. But first we ask what bounds can be placed on the social interaction effects without estimating the correlation parameter and instead restricting ρ to lie within a plausible range of values. As a lower bound, we assume $\rho \geq 0$, since the within-pair correlations in the observed determinants of behavior are all nonnegative (table 2). Under this assumption, the estimates of $\gamma_1 = .20$ and $\gamma_2 = .27$ from our baseline model with ρ constrained to equal 0 (table 3, column 3) provide upper bounds on the social interaction effects.

In choosing a plausible upper bound for ρ (and thus lower bounds for γ_1 and γ_2), we follow Altonji, Elder, and Taber (2005), who show that if the observed determinants of an outcome are a random subset of all determinants, then on average, the correlation in the unobservable determinants is equal to the correlation in the observed determinants. They also argue that in contexts where the observed covariates are chosen nonrandomly, their correlation might reasonably be viewed as an upper bound on the correlation of the unobservables.

In our baseline model for sexual behavior, the correlation of the estimated indexes of observables is 0.34. Figure 2A plots the point estimates of γ_1 and γ_2 and the profile likeli-

FIGURE 2.—ESTIMATES OF γ_1, γ_2, AND MAXIMIZED LOG LIKELIHOOD FOR ALTERNATIVE CHOICES OF CORRELATION PARAMETER

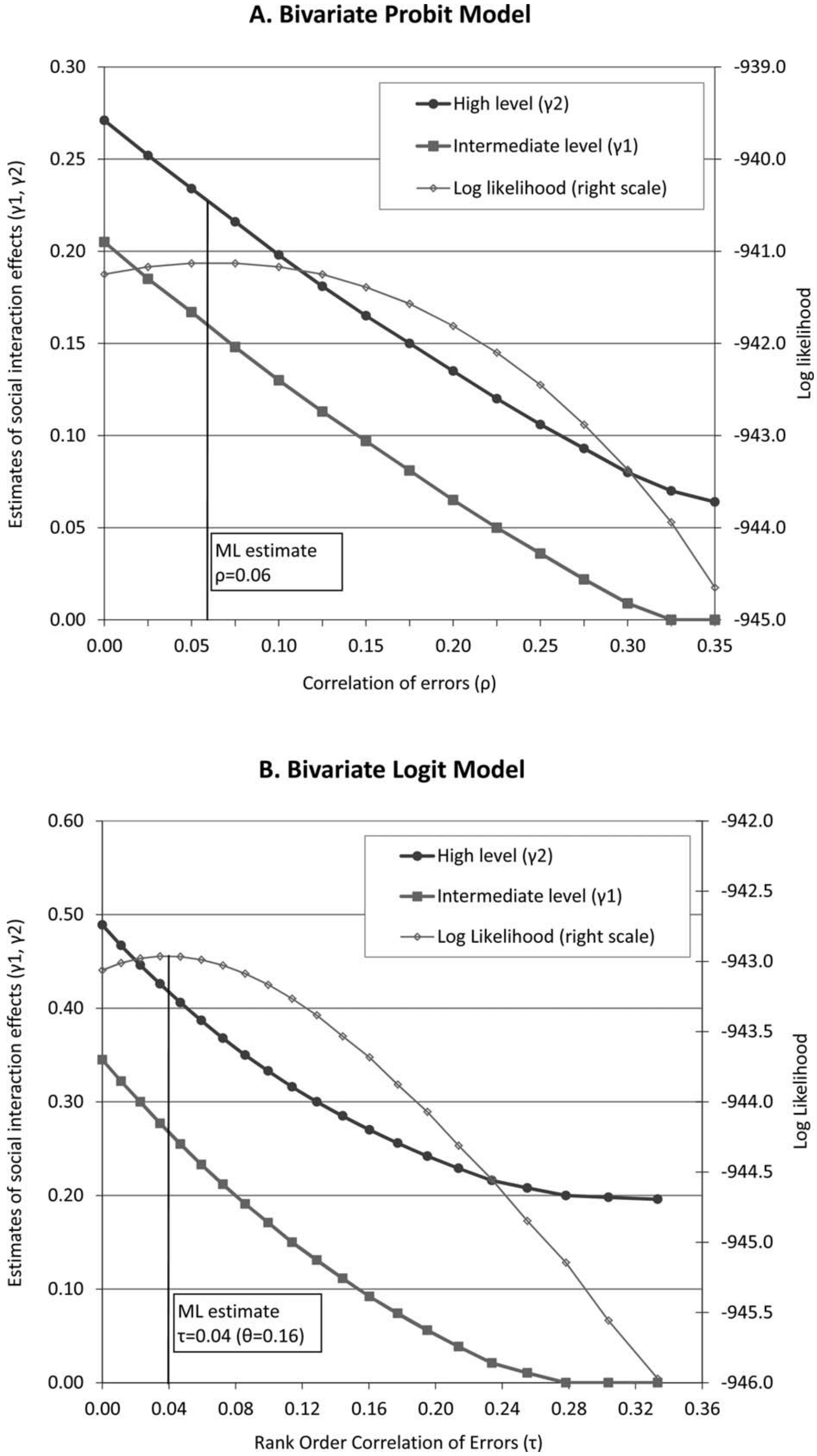


TABLE 7.—FALSIFICATION TEST FOR BIVARIATE ORDERED PROBIT MODELS OF SEXUAL ACTIVITY

	Original Estimation Sample				False Friend Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Error correlation (ρ)	–	0.28 (0.07)	–	0.14 (0.11)	–	0.19 (0.07)	–	0.19 (0.07)
Social interaction effect								
Intermediate level of activity (γ_1)	–	–	0.23 (0.06)	0.12 (0.10)	–	–	0.11 (0.06)	0.00 (0.00)
High level of activity (γ_2)	–	–	0.29 (0.08)	0.18 (0.10)	–	–	0.06 (0.08)	0.00 (0.00)
Attitude to risk	0.13 (0.03)	0.12 (0.04)	0.13 (0.04)	0.12 (0.04)	0.13 (0.04)	0.12 (0.04)	0.13 (0.04)	0.12 (0.04)
Physical development index	0.26 (0.05)	0.26 (0.05)	0.26 (0.05)	0.26 (0.05)	0.26 (0.05)	0.25 (0.05)	0.26 (0.05)	0.25 (0.05)
Log likelihood	−980.62	−971.42	−970.05	−969.35	−980.62	−976.74	−979.07	−976.74
Goodness of fit (nine cells)	27.62	4.15	2.40	0.56	14.95	4.13	10.13	4.13

Standard errors, clustered by school, in parentheses. The original estimation sample (columns 1–4) has 738 friend pairs who had not engaged in intercourse or intimate contact by wave 1. The false friends sample (columns 5–8) is constructed from the same set of respondents as the original sample and has 738 pairs of adolescents with similar propensities to initiate sexual activity (see the text for details). The dependent variable is an ordered variable indicating intimate touching, intercourse, or neither. All models include two constants and person-specific controls for attitude to risk and physical development. In models estimated using the false friend sample (columns 5–8), the error correlation is positive by construction. However, only three of the false friend pairs are actually best friends, and less than 4% of them attend the same school; hence, the social interaction effects in this sample are expected to be close to 0.

hood for values of ρ from 0 to 0.35 for the bivariate ordered probit model with baseline covariates. Both γ_1 and γ_2 are decreasing in ρ, while the likelihood is maximized at $\rho = 0.06$ (consistent with the results in column 4 of table 3). At the upper limit, we obtain a small positive social interaction effect for the high level of sexual activity ($\gamma_2 = 0.06$) and an estimate of 0 for the effect of the intermediate level of activity. In our context, however, we suspect that a value of $\rho = 0.34$ is rather extreme, since much of the correlation in sexual behavior is due to three exogenous characteristics—gender, race, and age—that define nearly nonoverlapping groups of potential best friends. When we control for gender, race, and age, the correlation in the index of observables is lower (0.22). As shown in figure 2A, fixing ρ at this value leads to estimates of $\gamma_1 = 0.05$ and $\gamma_2 = 0.12$. We view these as more reasonable lower bounds for the social interaction effects.

B. *Falsification Test*

In this section, we present a test of our model's ability to distinguish unobserved heterogeneity from state dependence using a sample of false friend pairs constructed from the data. This sample is constructed such that determinants of sexual activity are correlated within pairs, but the social interaction effects are expected to be 0. We start with all of the respondents who belong to one of the friend pairs in our analysis of sexual initiation and estimate an ordered probit model for sexual initiation with the expanded set of covariates. We then rank the individuals by the index of covariates from this model and pair off consecutive individuals to form a sample of 738 false friend pairs. This procedure ensures that the index of covariates is correlated within pairs, but the resulting false friends are unlikely to interact socially with one another. Indeed, only 3 of the 738 original friend pairs are reproduced in this sample, and less than 4% of the new pairs attend the same school.

Table 7 shows estimates from bivariate ordered-probit models similar to those in table 3 except that they control for only two variables: the physical development index and attitude toward risk. For reference, columns 1 to 4 show the estimates based on the true friends sample but using only these two covariates as controls. In the specification that allows both unobserved heterogeneity and social interaction effects (column 4), the estimate of ρ is larger than in the corresponding specification of table 3, which is unsurprising given that most of the original covariates (including age, gender, and race) are now part of the error term. The estimates of the social interaction effects are similar to the baseline estimates, though they are a little smaller and their standard errors are a little larger.

Turning to the estimates for the false friends sample, we see that in the model with both correlated heterogeneity and peer effects, the estimate of ρ is relatively large and positive (0.19, $t = 2.7$) while the social interaction effects lie on the boundary of the parameter space ($\gamma_1 = \gamma_1 = 0$). Moreover, allowing for unobserved heterogeneity greatly improves the fit of the model (compare columns 5 versus 6 and 7 versus 8), whereas the inclusion of social interaction effects does not (compare columns 5 versus 7 and 6 versus 8). These results are exactly what we would expect in a sample of false friends. Hence, they confirm that our statistical models can successfully distinguish between correlated heterogeneity and peer effects, giving us additional confidence in our conclusion that the correlation in sexual behavior between actual best friends is largely attributable to peer effects.

C. *Bivariate Ordered-Logit Model*

A critical feature of our structural model is the assumption of a parametric distribution for the unobserved heterogeneity components ε_1 and ε_2. In this section, we assess the robustness of our inferences by switching from a bivariate

TABLE 8.—COMPARISON OF BIVARIATE ORDERED PROBIT AND BIVARIATE ORDERED LOGIT MODELS FOR SEXUAL ACTIVITY BY FRIEND PAIRS

	Ordered Probit Models				Ordered Logit Models			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Error correlation parameter	–	0.24	–	0.06	–	0.58	–	0.16
(ρ for probit models, θ for logit models)		(0.06)		(0.09)		(0.13)		(0.35)
Social interaction effect								
Intermediate level of activity (γ_1)	–	–	0.20	0.16	–	–	0.35	0.27
			(0.05)	(0.08)			(0.11)	(0.19)
High level of activity (γ_2)	–	–	0.27	0.22	–	–	0.49	0.42
			(0.06)	(0.09)			(0.14)	(0.19)
Log likelihood	−949.86	−943.75	−941.25	−941.12	−951.65	−946.26	−943.06	−942.96
Implied rank-order correlation of latent errors in bivariate logit (τ)	–	–	–	–	0.00	0.15	0.00	0.04

Standard errors, clustered by school, in parentheses. See the text for model descriptions. In the sample are 738 friend pairs who had not engaged in intercourse or intimate contact by wave 1. The dependent variable is an ordered variable indicating intimate touching, intercourse, or neither. All models include two constants and sixteen other person-specific controls. Ordered logit models use Ali-Mikhail-Haq (1978) copula, with correlation parameter θ. This parameter can range from −1 to 1, with a value of $\theta = 0$, implying uncorrelated errors. The bottom row of the table shows the implied rank-order correlation of latent errors of two friends, using a formula from Kumar (2010).

normal to a generalized bivariate logit distribution. We use the copula function proposed by Ali et al. (1978) (AMH) to form a correlated bivariate logit.[27] For variates ε_1 and ε_2 distributed on $\mathbf{R}^2$, the AMH distribution function is

$$F(\varepsilon_1, \varepsilon_2; \theta) = [\,1 + \exp(-\varepsilon_1) + \exp(-\varepsilon_2) + (1-\theta) \times \exp(-\varepsilon_1 - \varepsilon_2)\,]^{-1},$$

where $\theta \in [-1, 1]$ is a measure of association.[28] As Kumar (2010) shows, the Kendall rank-order correlation (τ) between ε_1 and ε_2 is a monotonic function of θ and can range from (approximately) −0.18 to 0.33, with $\tau = 0$ when $\theta = 0$.[29]

Estimation results for bivariate ordered logit models are presented in table 8. For reference, the first four columns of the table reproduce the ordered probit models in columns 1 to 4 of table 3. Columns 5 to 8 show a parallel set of specifications with bivariate logistic errors. Note that the ρ parameter in the ordered probit models is a direct measure of the correlation between ε_1 and ε_2, whereas the θ parameter in the ordered logit models is scaled differently. To facilitate comparisons, the bottom row of the table shows the implied rank-order correlations between ε_1 and ε_2 from the estimated logit models. Similarly, the social interaction parameters in the logit model are scaled differently. In our sample, we expect the logit coefficients to be roughly two times bigger than the corresponding probit coefficients.

Comparisons between the corresponding columns of table 8 show that inferences about the relative importance of social interaction effects and correlated heterogeneity are highly robust to changes in the assumed error distribution. In particular, whether we assume normal or logistic errors, the data suggest that the correlation in the outcomes of best friend pairs is mainly attributable to peer effects rather than to correlated heterogeneity. Figure 2B shows the profiled likelihood and associated estimates of the interaction effects γ_1 and γ_2 for the bivariate ordered logit as we vary the value of the parameter θ. (For ease of interpretation, the *x*-axis shows the rank-order correlation coefficient τ for each choice of θ.) The graph looks very similar to figure 2A and suggests that even for extreme values of the correlation parameter ($\theta = 1$, corresponding to $\tau = 0.33$) there is a sizable social interaction effect on the highest level of sexual activity (intercourse).

D. *Models with no Exclusion Restrictions*

As noted in section II, our structural model is identified partly through exclusion restrictions. Thus far, we have exploited these restrictions by assuming that all the *X*'s for one friend are excluded from the other's equation. In this section, we examine the robustness of our results by estimating models without any exclusion restrictions. Here, the estimates of ρ, γ_1, and γ_2 are driven entirely by the nonlinearities inherent in the model. We first estimate models in which the *X*'s for each friend are allowed to directly affect the other friend. Then we estimate a stripped-down model with only two shared covariates: the gender of the pair and their average age.

Estimates from these models are presented in table 9. In the specifications that include all *X*'s for both friends (columns 3 and 4), the estimate of γ_2 remains relatively large and at least marginally significant. The estimate of γ_1 is no longer significant but is always within ½ of a standard error of the baseline estimates of 0.15 or 0.16. And the estimate of ρ is a little higher than the baseline estimates but not significantly so. In the specification that controls for only gender and average age (column 5), the estimate of ρ is substantially larger, but this is expected given that the model omits several correlated determinants of sexual initiation.

[27] Nelsen (2006) presents an overview of the use of copula functions to construct generalized multivariate distributions. The AMH copula is $C(u_1, u_2; \theta) = u_1 u_2 / [1 - \theta\,(1-u_1)\,(1-u_2)]$.

[28] Note that the marginal distribution functions $F(\varepsilon_1, \infty; \theta)$ and $F(\infty, \varepsilon_2; \theta)$ are standard logistic functions.

[29] The formula is: $\tau = (3\theta-2)/3\theta - [(2(1-\theta)^2 \ln(1-\theta)]/3\theta^2$. Kumar (2010) also shows the relationship between θ and the Pearson correlation coefficient between ε_1 and ε_2. This can range from −0.27 to 0.48 and is 0 when $\theta = 0$.

TABLE 9.—BIVARIATE ORDERED PROBIT MODELS FOR SEXUAL ACTIVITY WITH ALTERNATIVE EXCLUSION RESTRICTIONS

	Baseline Models from Table 3		No Excluded Variables: Both Equations Contain all of X_1s and X_2s		No Excluded Variables: Both Equations Contain Only Gender and Average Age
	(1)	(2)	(3)	(4)	(5)
Include wave 1 behaviors?	No	Yes	No	Yes	No
Error correlation (ρ)	0.06	0.02	0.13	0.06	0.17
	−(0.09)	−(0.10)	(0.09)	(0.10)	(0.09)
Social Interaction					
Intermediate level of activity (γ_1)	0.16	0.15	0.10	0.11	0.10
	−(0.08)	(0.08)	(0.08)	(0.08)	(0.07)
High level of activity (γ_2)	0.22	0.21	0.17	0.18	0.16
	−(0.09)	(0.09)	(0.09)	(0.09)	(0.08)
Log likelihood	−941.12	−888.63	−925.85	−873.74	−984.53
Chi squared	0.94	0.47	0.46	0.34	0.52

Standard errors, clustered by school, in parentheses. See notes to table 3. Models in columns 3 and 4 allow all *X*'s of each friend to affect the other. Models in column 5 control only for the gender of the pair and their average age.

However, the estimates of the gammas from this specification are very similar to those in columns 3 and 4.[30]

Overall, we conclude that estimates of the key social interaction parameters from specifications that rely entirely on functional form assumptions are close to the estimates obtained from specifications that impose both exclusion restrictions and functional form assumptions. Our Monte Carlo results suggested that if the model specification is correct (we have both the correct functional forms and the correct exclusion restrictions), then we would expect similar results from the two classes of models. We therefore interpret the results in table 9 as affirming the overall validity of our parametric model and the exclusion restrictions imposed in our main specifications.

VI. Models That Address Sample Selection or Allow for Heterogeneous Peer Effects

Our estimation sample is restricted to friend pairs with minimal sexual experience at the wave 1 interview. In this section, we consider the implications of this sample restriction for the generalizability of our results. As we have already seen, there are some significant observable differences between our sample and the broader sample of friend pairs that can be matched in Add Health; in particular, our sample is younger and contains more females. Unobservable features of our sample could also affect our estimates. For example, the similarity in baseline levels of sexual activity between friends in our sample might be partly due to a relatively high propensity to imitate one another's behavior.

To assess the potential importance of sample selection biases, we estimated a series of two-step selection models (Heckman, 1979) that include a control function constructed using estimates from a first-step probit model for the probability of being included in our estimation sample.[31] The estimated coefficients on the control function were uniformly insignificant, providing no indication of selectivity biases in our main specifications. Moreover, the estimates of ρ, γ_1, and γ_2 from these models were almost identical to those in table 3.

Next, we estimate a series of models that allow the peer effects between a pair of friends to vary with observed characteristics of either the pair or the individual. Because the pairs in our sample are disproportionately female and relatively young, we start by allowing the effects to vary with the gender of the pair and their average age. We also consider two other variables that are likely to influence the size of the peer effects: the stability of the friendship and whether the friendship is reciprocated.

We allow a variable Z to influence the peer effects by estimating models in which

$$\gamma_1 = \exp(\mathrm{a} + \mathrm{bZ}), \tag{5a}$$

$$\gamma_2 = \exp(\mathrm{c} + \mathrm{dZ}). \tag{5b}$$

For simplicity, we assume that the unobserved determinants of friends' behavioral choices are uncorrelated.[32]

The results from these models are presented in table 10. The top panel shows the estimates for the parameters in equations (5a) and (5b), while the lower panel shows the implied peer effects for different types of friend pairs. The gender interaction terms (column 1), though not significant by conventional standards, suggest that peer effects are larger for females than for males and that there are especially large gender differences in peer effects for the initiation of

[30] In Card and Giuliano (2011) we present additional evidence supporting the robustness of our results to varying the exclusion restrictions (see table 8 and table A4a).

[31] The first-stage probit included all the baseline characteristics of both friends (32 variables) and was estimated on the full sample of 1,689 matched friend pairs. The second-stage models are the same as the ones in table 3, with the addition of a control function based on parameters from the first-stage model.

[32] We have also tried allowing for heterogeneity in the correlation coefficient by estimating separate models for different subsamples, but these estimates are variable and imprecise.

TABLE 10.—BIVARIATE ORDERED PROBIT MODELS WITH HETEROGENEITY IN THE PEER EFFECTS

	Heterogeneity Variable			
	Indicator for Male Friends	Average Age of Friends	Predicted Probability of Being Reciprocated Best Friends in W2	Indicator for Respondents Who Did not Reciprocate Friend's Nomination
	(1)	(2)	(3)	(4)
Equation for γ_1				
Constant (a)	−1.22	0.85	−2.23	−1.42
	(0.24)	(2.72)	(0.19)	(0.26)
Coefficient on variable (b)	−1.05	−0.16	3.25	−0.68
	(0.85)	(0.18)	(0.62)	(0.71)
Equation for γ_2				
Constant (c)	−0.89	3.15	−2.06	−1.17
	(0.21)	(1.65)	(0.15)	(0.20)
Coefficient on variable (d)	−1.31	−0.29	3.25	−0.53
	(0.75)	(0.11)	(0.55)	(0.48)
Log likelihood	−938.10	−938.65	−937.32	−940.38
Implied peer effects for representative groups				
	Females	Younger (age 14)	High Probability ($p = 0.35$)	Reciprocated
γ_1	0.30	0.25	0.34	0.24
γ_2	0.41	0.38	0.40	0.31
	Males	Older (age 17)	Low Probability ($p = 0.10$)	Did Not Reciprocate
γ_1	0.10	0.16	0.15	0.12
γ_2	0.11	0.16	0.18	0.18

See the note to table 3. Standard errors, clustered by school, in parentheses. All models include two constants and sixteen person-specific controls. Models for peer effects are parameterized as $\gamma_1 = \exp(a + bZ)$, $\gamma_2 = \exp(c + dZ)$. See the text.

sexual intercourse. The age interaction terms (column 2) also suggest heterogeneous peer effects: they imply that the effects are larger among younger friend pairs, especially for the initiation of intercourse. However, while the gender results are robust to different model specifications, the age interaction coefficients become insignificant or change sign in models with additional controls.[33]

Column 3 examines the role of friendship stability, which is measured by the predicted probability that the two friends nominate each other as best friends in the second wave of the survey.[34] We estimate this probability using a simple probit model that includes means and absolute differences in the friends' characteristics, indicators for the source of friendship nominations used to construct the match, and a dummy for whether the nomination was reciprocated in wave 1. The heterogeneity estimates imply significantly stronger peer effects in friendships that are more likely to be reciprocated one year later.[35] Finally, column 4 allows the strength of the peer effects experienced by a respondent to depend on whether she reciprocated the friendship nomination of her friend. The estimates imply large asymmetries. Indeed, they suggest that students whom we assign to a friendship but did not reciprocate the nomination experience negligible peer effects.

Further evidence of asymmetries is seen in table 11. The first two columns of the table show that estimates for our baseline model (the model in column 4 of table 3) fit separately for reciprocated and nonreciprocated friend pairs. The estimated social interaction effects and the estimated correlation parameter are all larger for reciprocated best friend pairs though relatively imprecise. In particular, the estimates of γ_2 imply that among reciprocated best friends, the likelihood of initiating intercourse increases by about 7 percentage points if one's best friend also does so, while among nonreciprocated pairs, the corresponding increase is only about 2.5 percentage points. The model in column 3, which is fit only to the nonreciprocating pairs, allows different values of γ_1 and γ_2 for the nominators and the (nonreciprocating) nominees in each pair. The estimates, while imprecise, suggest that the nominator experiences relatively strong social interaction effects (roughly a 3.5 percentage point change in the likelihood of initiating intercourse), whereas the nonreciprocator experiences relatively weak effects (roughly 1.5 percentage points). This asymmetry suggests that there is valuable information in the friend networks named by each member of the pair, though given the small sample sizes, we cannot make strong inferences.[36]

[33] Estimates from models that control for wave 1 GPA and other wave 1 behaviors are reported in Card and Giuliano (2011, table 9).

[34] We use a predicted measure of friendship stability instead of an ex post measure because the stability of the friendship itself may be affected by the degree of similarity in the friends' behavioral choices between waves.

[35] These results suggest that estimates for the full sample may be attenuated by changes in friendships that occur between wave 1 and wave 2. In principle, one could model both the choice of friend and choice of behavior as a joint decision. However, this is not practical in our sample given the small number of friends and the limited information about the set of potential friends in wave 2.

[36] It is worth noting that previous studies have assumed that the direction of peer influence can be inferred from asymmetries in friendship nominations and have used this assumed directionality to identify peer effects in spatial autoregressive models (see Bramoulle et al., 2009; Lin, 2010). To our knowledge, ours is the first study to provide evidence of such directionality.

TABLE 11.—ESTIMATED BIVARIATE ORDERED PROBIT MODELS, FIT BY SUBGROUP

	Reciprocated Pairs Only	Nonreciprocated Pairs Only: Symmetric Effects	Nonreciprocated Pairs Only: Asymmetric Effects
	(1)	(2)	(3)
Error correlation (ρ)	0.13	0.07	0.06
	(0.25)	(0.13)	(0.13)
Social interaction effect			
Intermediate level of activity (γ_1)	0.25	0.07	
	(0.10)	(0.09)	
High level of activity (γ_2)	0.33	0.11	
	(0.06)	(0.10)	
Intermediate level of activity (γ_1)—Nominators			0.10
			(0.12)
High level of activity (γ_2)—Nominators			0.17
			(0.12)
Intermediate level of activity (γ_1)—Nonreciprocators			0.03
			(0.09)
High Level of activity (γ_2)—Nonreciprocators			0.05
			(0.12)
Log Likelihood	−319.6	−610.26	−609.87
N	265	473	473

See notes to table 3. Standard errors, clustered by school, in parentheses. In nonreciprocating friend pairs, the nominator is the friend who named the other as his or her best friend; the nonreciprocator failed to name the nominator as his or her best friend.

VII. Estimation Results for Other Risky Behaviors

In this final section, we briefly summarize the estimation results for models of the interactions in other forms of risky behavior, using bivariate ordered probit models similar to those estimated in table 3 for sexual initiation. Panels A, B, and C of table A4 present results for cigarette smoking, marijuana use, and truancy, respectively. In each case, the estimation sample includes only friend pairs in which neither friend was engaging in the behavior (at either an intermediate or high level) as of wave 1. As in table 3, we show models with our baseline controls and a parallel set that include GPA and indicators for the other risky behaviors as of wave 1.

The results for cigarette smoking are similar to those for initiation of sex in several ways. First, the models with social interactions provide slightly larger likelihood values and improved goodness of fit compared to the models with only correlated heterogeneity. Second, the specifications with social interactions imply stronger peer effects for the more intense level of activity (here, regular cigarette smoking). And third, as in table 3, the specifications that control for other risky behaviors in wave 1 produce estimates that are very similar to those from the baseline model. However, the models for cigarette smoking that include both correlated heterogeneity and peer effects (columns 4 and 8) yield larger estimates of the correlation parameter than those found in the models of sexual activity, and the social interaction estimates in these specifications are not statistically significant. These results are less conclusive than the results for sex about the presence of peer effects and suggest that some of the correlation patterns in cigarette smoking may be due to common unobserved heterogeneity.

The estimated models of marijuana use are very different from the models for sex and tobacco. First, the models that include social interaction effects fit the data much better than the model with only correlated heterogeneity. Second, the estimates for γ_1 are much larger than those for γ_2, suggesting that peer effects are larger for experimental use than for regular use. And third, the models that include both correlated heterogeneity and peer effects produce negative estimates for the correlation parameter. This last result is counterintuitive and makes the estimates from the combined model difficult to interpret. One potential explanation is that marijuana use is less precisely measured in the Add Health survey than other risky behaviors, and as a result, our classification of individuals as experimental or regular marijuana users may be subject to a relatively large degree of measurement error.[37]

Finally, the models for truancy behavior also differ somewhat from the models for sex and cigarette smoking. Truancy is even more highly correlated within friend pairs than the other risky behaviors. (A simple chi squared statistic for the 3×3 table of joint truancy behavior has the highest value of all four behaviors, 49.4). And here, the models that allow both correlated heterogeneity and peer effects fit better than either model that allows just one of these factors. Although the parameter estimates from these flexible models are relatively imprecise, the point estimates suggest that both factors may be present. Finally, the estimates of γ_1 and

[37] Our definition of *experimental use* is based on whether the respondent indicates having tried marijuana as of the wave 2 interview, and our definition of *regular use* is based on whether the respondent indicates having used one or more times in past thirty days. Thus, respondents who tried marijuana for the first time in the past thirty days may be misclassified as regular users, while more regular users may be classified as experimental users if they went for thirty days without using.

γ_2 suggest that the peer effect for skipping school once is slightly larger than the peer effect for more regular truancy behavior.

VIII. Summary and Conclusion

We have presented a simple approach to estimating social interaction effects in the risky behavior of adolescent best friend pairs, based on econometric models of their joint outcomes that allow for correlated unobserved heterogeneity. Methodologically, our models extend the bivariate discrete choice approach developed by Bresnahan and Reiss (1990) and Tamer (2003) to an ordered choice framework. Our identification approach relies on a combination of exclusion restrictions and functional form assumptions (including a parametric distribution for unobserved heterogeneity) to empirically distinguish between social interaction effects and correlated heterogeneity. We present a series of checks to assess the robustness of our findings, including a falsification exercise based on artificially constructed friend pairs and comparisons between models with bivariate normal and generalized logistic distributions.

An important feature of our approach is that we use naturally occurring friendships of the kind that mediate many forms of adolescent behavior. An alternative identification strategy employed in a number of recent studies relies on randomly assigned peer groups such as college roommates or classmates. While much can be learned from such designs, it is unclear whether the social interaction effects observed from the behavior of individuals assigned to random peer groups adequately represent the peer effects experienced in naturally occurring friendships. Indeed, Carrell et al. (2011) show that the reduced-form estimates from such studies can be difficult to interpret because they depend on the patterns of association that emerge after random assignment, depending on the structure of the constructed peer group.

Our empirical results suggest that adolescent friends' decisions to become sexually active exhibit important interaction effects. Having a best friend who is engaging in intercourse, for example, raises the likelihood that a previously inexperienced adolescent also engages in intercourse by nearly 5 percentage points. Overall, we estimate that about 10% of inexperienced adolescents make a decision about sexual initiation based directly on the choice of their best friend. We find similar peer effects in other risky behaviors, including the use of tobacco and marijuana and truancy.

We also find evidence of heterogeneity in the magnitude of the peer effects between friends. Not surprisingly, the effects are strongest between best friends in reciprocated friendships. In nonreciprocated friend pairs, the effects are asymmetric: the person who nominates the other as a best friend experiences a relatively strong social interaction effect, whereas the nonreciprocator experiences a weak effect. This pattern of heterogeneity suggests that the relatively small peer effects observed in many previous studies that rely on random or quasi-random manipulation of peer groups may be due in part to weaker social interaction effects between people who are not as closely connected as best friends. More generally, our findings underscore the potential importance of allowing peer effects to depend on the strength of the connections between people.

REFERENCES

Akerlof, George A., "Social Distance and Social Decisions," *Econometrica* 65:5 (1997), 1005–1027.

Ali, Mir M., N. N. Mikhail, and M. Safiul Haq, "A Class of Bivariate Distributions Including the Bivariate Logit," *Journal of Multivariate Analysis* 8 (1978), 405–412.

Altonji, Joseph, Todd Elder, and Christopher Taber, "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools," *Journal of Political Economy* 113:1 (2005), 151–184.

Argys, Laura M., and Daniel I. Rees, "Searching for Peers' Effects: A Test of the Contagion Hypothesis," this REVIEW 90:3 (2008), 442–458.

Bajari, Patrick, Han Hong, and Stephen P. Ryan, "Identification and Estimation of a Discrete Game of Complete Information," *Econometrica* 78:5 (2009), 1529–1568.

Berndt, Thomas J., "The Features and Effects of Friendship in Early Adolescence," *Child Development* 53 (1982), 1447–1460.

Bjorn, P., and Q. Vuong, "Simultaneous Equations Models for Dummy Endogenous Variables: A Game Theoretic Formulation with Application to Labor Force Participation," Social Science working paper 537, California Institute of Technology (1984).

Bramoulle, Yann, Habiba Djebbari, and Bernard Fortin, "Identification of Peer Effects through Social Networks." *Journal of Econometrics* 150:1 (2009), 41–55.

Bresnahan, Timothy F., and Peter C. Reiss, "Entry in Monopoly Markets," *Review of Economic Studies* 57 (1990), 531–553.

——— "Empirical Models of Discrete Games," *Journal of Econometrics* 48 (1991), 57–81.

Card, David, and Laura Giuliano, "Peer Effects and Multiple Equilibria in the Risky Behavior of Friends," NBER working paper 12915 (2011).

Carrell, Scott E., Richard L. Fullerton, and James E. West, "Does Your Cohort Matter? Estimating Peer Effects in College Achievement," *Journal of Labor Economics* 27:3 (2009), 439–464.

Carrell, Scott E., Bruce I. Sacerdote, and James E. West, "From Natural Variation to Optimal Policy? The Lucas Critique Meets Peer Effects," NBER working paper 16865 (2011).

Ciliberto, Federico, and Elie Tamer, "Market Structure and Multiple Equilibria in Airline Markets," *Econometrica* 77:6 (2009), 1791–1828.

De Glorgi, Giacomo, Michele Pellizzari, and Silvia Redaelli, "Identification of Social Interactions through Partially Overlapping Peer Groups," *American Economic Journal: Applied Econometrics* 2 (2010), 241–275.

Fryer, Roland G., and Paul Torelli, "An Empirical Analysis of Acting White," *Journal of Public Economics* 94:5–6 (2010), 380–396.

Gumbel, E. J., "Bivariate Logit Distributions," *Journal of the American Statistical Association* 56:294 (1961), 335–349.

Harris, K. M., C. T. Halpern, E. Whitsel, J. Hussey, J. Tabor, P. Entzel, and J. R. Udry, "The National Longitudinal Study of Adolescent Health: Research Design" (2009), http://www.cpc.unc.edu/projects/addhealth/design.

Halliday, Timothy J., and Sally Kwak, "Weight Gain in Adolescents and Their Peers," *Economics and Human Biology* 7 (2009), 181–190.

Haynie, Dana L., "Delinquent Peers Revisited: Does Network Structure Matter?" *American Journal of Sociology* 104:4 (2001), 1013–1057.

Heckman, James J., "Statistical Models for Discrete Panel Data Developed and Applied to Test the Hypothesis of True State Depen-

dence against the Hypothesis of Spurious State Dependence," *Annales de l'inseé* 30/31 (1978), 227–269.
——— "Sample Selection Bias as a Specification Error," *Econometrica* 47 (1979), 153–161.
——— "Statistical Models for Discrete Panel Data" (pp. 114–175), in Charles F. Manski and Daniel McFadden, eds., *Structural Analysis of Discrete Data with Econometric Applications* (Cambridge, MA: MIT Press, 1981).
Huang, Ching-I, "Intra-Household Effects on Demand for Telephone Service: Empirical Evidence" (2010), http://ssrn.com/abstract=991772.
Hyslop, Dean R., "State Dependence, Serial Correlation and Heterogeneity in Intertemporal Labor Force Participation of Married Women," *Econometrica* 67 (1999), 1255–1294.
Jacob, Brian, "Public Housing, Housing Vouchers and Student Achievement: Evidence from Public Housing Demolitions in Chicago," *American Economic Review* 94:1 (2004) 233–258.
Kling, Jeffrey R., Jeffrey B. Liebman, and Lawrence F. Katz, "Experimental Analysis of Neighborhood Effects," *Econometrica*, 75:1 (2007), 83–119.
Krauth, Brian V., "Simulation-Based Estimation of Peer Effects," *Journal of Econometrics* 133 (2006), 243–271.
——— "Peer and Selection Effects on Youth Smoking in California," *Journal of Business and Economic Statistics* 25:3 (2007), 288–298.
Kremer, Michael, and Dan Levy, "Peer Effects and Alcohol Use among College Students," *Journal of Economic Perspectives* 22:3 (2008), 189–206.
Kumar, Pranesh, "Probability Distributions and the Estimation of Ali-Mikhail-Haq Copula," *Applied Mathematical Statistics* 4:14 (2010), 657–666.
Lin, Xu, "Identifying Peer Effects in Student Academic Achievement by Spatial Autoregressive Models with Group Unobservables," *Journal of Labor Economics*. 28:4 (2010), 825–860.
Manski, Charles F., "The Identification of Endogenous Social Effects: The Reflection Problem," *Review of Economic Studies* 60 (1993), 531–542.
Moffitt, Robert, "Policy Interventions, Low-level Equilibria, and Social Interactions" (pp. 45–82), in Steven Durlauf and Peyton Young, eds., *Social Dynamics* (Cambridge, MA: MIT Press, 2001).
Nelsen, Roger B., *An Introduction to Copulas* (New York: Springer, 2006).
Oreopoulos, Philip, "The Long Run Consequences of Growing Up in a Poor Neighbourhood," *Quarterly Journal of Economics* 118:4 (2003), 1533–1575.
Sacerdote, Bruce I., "Peer Effects with Random Assignment: Results for Dartmouth Roommates," *Quarterly Journal of Economic* 116:2 (2001), 681–704.
Smith, Kirsten P., and Nicholas Christakis, "Social Networks and Health," *Annual Review of Sociology* 34 (2008), 405–429.
Soetevent, Adriaan R., and Peter Kooreman, "A Discrete Choice Model with Social Interactions: An Analysis of High School Teen Behavior," *Journal of Applied Econometrics* 22 (2006), 599–624.
Stinebrickner, Ralph, and Todd R. Stinebrickner, "What Can Be Learned about Peer Effects Using College Roommates? Evidence from New Survey Data and Students from Disadvantaged Backgrounds," *Journal of Public Economics* 90:8–9 (2006), 1435–1454.
Tamer, Elie, "Incomplete Simultaneous Discrete Response Model with Multiple Equilibria," *Review of Economic Studies* 70 (2003), 147–165.
Zimmerman, David, "Peer Effects in Academic Outcomes: Evidence from a Natural Experiment," this REVIEW 85:1 (2003), 9–23.

APPENDIX

Description of the Monte Carlo Study

This appendix describes in more detail the Monte Carlo study we conducted to probe the identification of social interaction effects and unobserved heterogeneity. The data-generating process (DGP) follows the model described in section IIb. Specifically, we simulate a pair of latent indexes:

$$y_1^* = X_1\beta + \varepsilon_1,$$
$$y_2^* = X_2\beta + \varepsilon_2,$$

where $(\varepsilon_1, \varepsilon_2)$ are distributed as bivariate normal with variances of 1 and correlation ρ, and X_1 and X_2 are also normally distributed, with variance of 1 and correlation of 0.4. In design 1, we choose $\beta = 0.5$, while in design 2, we choose $\beta = 0$. The value of $\beta = 0.5$ was selected to approximate the power of the observed covariates in our actual sample, which yield a pseudo-R^2 of 0.08 in a simple ordered probit model for the observed sexual initiation behavior. Given (y_1^*, y_2^*), we then generate the observed outcomes (y_1, y_2) using the thresholds described by equations (3a) and (3b), with interaction parameters γ_1 and γ_2. We select the constants c_{10} and c_{20} to yield the same average fractions for each level of activity as in our actual sample.

For DGP 1, we set $\gamma_1 = 0.20$, $\gamma_2 = 0.25$, and $\rho = 0$. For DGP 2, we set $\gamma_1 = \gamma_2 = 0$ and $\rho = 0.25$. For DGP 3 we set $\gamma_1 = 0.10$, $\gamma_2 = 0.15$, and $\rho = 0.15$. In regions of multiple equilibria (regions A and B of figure 1), we assume that the friends choose the higher activity level 50% of the time. The combinations of parameters $(\gamma_1, \gamma_2, \rho)$ for each of the three DGPs are selected to yield a predicted distribution for $y_1 \times y_2$ that is approximately equal to the observed joint distribution of sexual activity as in our sample.

We simulate 100 samples of size 1,000 and estimate the model, treating γ_1, γ_2, ρ, c_{10}, c_{20}, and β as unknown parameters. In the estimation procedure, we restrict $\gamma_1 \geq 0$, $\gamma_2 \geq 0$, and $-1 \leq \rho \leq 1$ by estimating parameters k_1, k_2, k_3, where $\gamma_1 = \exp(k_1)$, $\gamma_2 = \exp(k_2)$, and $\rho = \tanh(k_3)$. We conduct the simulations using STATA: the model is estimated using the "ml" command, with a combination of the Broyden-Fletcher-Goldfarb-Shanno (BFGS) and Newton-Raphson algorithms.

Table A1 summarizes the empirical distributions of the estimated parameters γ_1, γ_2, and ρ for each DGP and design. We show the median and mean estimation errors as well as the standard deviation of the parameter estimates across replications. The results suggest that a sample of size 1,000 is sufficient to ensure that the maximum likelihood estimates are centered close to their true values for each DGP and that the expected root-mean-squared sampling error for each parameter is on the order of 0.05 to 0.10. A comparison between the two designs also shows that the availability of an excluded covariate (as in design 1) leads to a notable reduction in the variability of the estimates of γ_1, γ_2, and ρ.

TABLE APPENDIX

TABLE A1.—EMPIRICAL DISTRIBUTIONS OF ESTIMATION ERRORS IN APPLICATION OF BIVARIATE ORDERED PROBITS TO THREE DGPS, WITH TWO ALTERNATIVE DESIGNS FOR THE COVARIATES

	Design 1: ($\sigma(X_1) = 0.50$) (1)	Design 2: ($\sigma(X_1) = 0.00$) (2)
1. DGP 1: $\gamma_1 = 0.20$, $\gamma_2 = 0.25$, $\rho = 0$		
a. Median/mean error in γ_1	−0.01 / −0.02	0.00 / −0.02
(SD)	(0.09)	(0.11)
b. Median/mean error in γ_2	−0.02 / −0.02	−0.03 / −0.04
(SD)	(0.10)	(0.10)
c. Median/mean error in ρ	0.01 / 0.02	−0.02 / 0.02
(SD)	(0.10)	(0.13)
2. DGP 2: $\gamma_1 = 0$, $\gamma_2 = 0$, $\rho = 0.25$		
a. Median/mean error in γ_1	0.00 / 0.02	0.00 / 0.03
(SD)	(0.03)	(0.05)
b. Median/mean error in γ_2	0.00 / 0.03	0.00 / 0.03
(SD)	(0.04)	(0.05)
c. Median/mean error in ρ	−0.02 / −0.02	−0.01 / −0.02
(SD)	(0.07)	(0.08)
3. DGP 3: $\gamma_1 = 0.10$ $\gamma_2 = 0.15$, $\rho = 0.15$		
a. Median/mean error in γ_1	0.00 / 0.00	0.00 / 0.01
(SD)	(0.06)	(0.09)
b. Median/mean error in γ_2	0.00 / 0.00	−0.01 / 0.01
(SD)	(0.09)	(0.10)
c. Median/mean error in ρ	0.00 / 0.00	−0.02 / −0.03
(SD)	(0.08)	(0.09)

Based on applications of maximum likelihood estimation of model with both unobserved heterogeneity and social interactions, with 100 simulations per DGP. See the text for details on the design of the data sets used in the simulations. Simulated data have 1,000 friend pairs.

TABLE A2.—DESCRIPTIVE STATISTICS FOR CIGARETTE SMOKING, MARIJUANA USE, AND TRUANCY

	BFs who Had Never Smoked a Cigarette as of Wave 1	BFs Who Had Never Tried Marijuana as of Wave 1	BFs Who Did not Skip Any Days of School in Wave 1
	(1)	(2)	(3)
Risky behaviors as of wave 1			
Intimate touching	0.25	0.27	0.28
Had intercourse	0.18	0.19	0.18
Tried cigarette smoking	0.00	0.25	0.30
Smoked cigarettes regularly	0.00	0.06	0.09
Tried marijuana	0.07	0.00	0.14
Used marijuana regularly	0.04	0.00	0.07
Drank alcohol without adult presence	0.16	0.24	0.29
Drank alcohol regularly	0.03	0.06	0.09
Skipped school one or more days	0.15	0.16	0.00
Skipped school two or more days	0.10	0.10	0.00
Risky behaviors as of wave 2			
Tried cigarette smoking	0.191		
Smoked cigarettes regularly	0.029		
Tried marijuana		0.098	
Used marijuana regularly		0.059	
Skipped school one or more days			0.155
Skipped school two or more days			0.081
Number of observations	1,476	2,152	1,928

Each column shows the means for the subsample of best friend pairs with minimal experience in the indicated activity as of wave 1 (W1).

TABLE A3.—ESTIMATED BIVARIATE ORDERED PROBIT MODELS FOR SEXUAL ACTIVITY BY FRIEND PAIRS

	Baseline				Expanded Set of Covariates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	0.07	0.07	0.06	0.06	0.03	0.03	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Male	0.04	0.05	0.04	0.05	0.03	0.04	0.04	0.04
	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
Black race	0.27	0.25	0.25	0.25	0.34	0.33	0.32	0.32
	(0.12)	(0.12)	(0.11)	(0.12)	(0.14)	(0.14)	(0.13)	(0.14)
Physcial development index	0.23	0.24	0.23	0.24	0.23	0.24	0.24	0.24
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Attitude toward risk	0.12	0.10	0.11	0.11	0.07	0.06	0.07	0.07
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Future orientation	−0.07	−0.07	−0.07	−0.07	−0.02	−0.02	−0.02	−0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Time preference	0.10	0.10	0.10	0.10	0.04	0.04	0.05	0.05
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Smokers in household	0.25	0.25	0.25	0.25	0.16	0.16	0.16	0.16
	(0.09)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)
Two-parent household	−0.21	−0.20	−0.20	−0.20	−0.20	−0.20	−0.20	−0.20
	(0.11)	(0.10)	(0.10)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
Frequency that parents attend church	−0.07	−0.06	−0.07	−0.06	−0.06	−0.05	−0.05	−0.05
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Parents not religious	−0.19	−0.13	−0.16	−0.15	−0.26	−0.22	−0.23	−0.23
	(0.22)	(0.21)	(0.22)	(0.21)	(0.20)	(0.20)	(0.20)	(0.20)
At least one parent finished high school	−0.24	−0.24	−0.24	−0.24	−0.26	−0.27	−0.26	−0.26
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)
At least one parent finished college	−0.12	−0.10	−0.11	−0.11	−0.08	−0.08	−0.08	−0.08
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
GPA for wave 1 school year					−0.08	−0.08	−0.08	−0.08
					(0.05)	(0.05)	(0.05)	(0.05)
Tried cigarette smoking as of wave 1					0.21	0.20	0.20	0.20
					(0.10)	(0.10)	(0.10)	(0.10)
Smoked cigarettes regularly as of wave 1					0.32	0.31	0.32	0.32
					(0.18)	(0.18)	(0.18)	(0.18)
Tried marijuana as of wave 1					0.12	0.12	0.11	0.11
					(0.17)	(0.17)	(0.17)	(0.17)
Used marijuana regularly as of wave 1					0.10	0.09	0.10	0.09
					(0.21)	(0.21)	(0.21)	(0.21)
Drank alcohol without adult presence as of wave 1					0.47	0.48	0.47	0.47
					(0.10)	(0.10)	(0.10)	(0.10)

TABLE A3.—(CONTINUED)

	Baseline				Expanded Set of Covariates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drank alcohol regularly as of wave 1					0.17	0.15	0.15	0.15
					(0.18)	(0.18)	(0.18)	(0.18)
Skipped school one or more days as of wave 1					0.37	0.37	0.36	0.36
					(0.14)	(0.14)	(0.14)	(0.14)
Skipped school two or more days as of wave 1					−0.06	−0.07	−0.07	−0.07
					(0.21)	(0.20)	(0.20)	(0.20)

See the note to Table 3.

TABLE A4.—SUMMARY OF BIVARIATE ORDERED PROBIT MODELS FOR RISKY BEHAVIORS OF FRIEND PAIRS

	Baseline				Expanded Set of Covariates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Cigarette smoking								
Error correlation (ρ)	–	0.22	–	0.09	–	0.21	–	0.10
		(0.09)		(0.14)		(0.10)		(0.14)
Social interaction effect								
Intermediate level of activity (γ_1)	–	–	0.20	0.12	–	–	0.18	0.10
			(0.09)	(0.13)			(0.10)	(0.14)
High level of activity (γ_2)	–	–	0.44	0.36	–	–	0.44	0.35
			(0.20)	(0.23)			(0.20)	(0.22)
Log likelihood	−809.79	−804.89	−803.72	−803.53	−782.28	−777.99	−776.99	−776.72
Goodness of fit (nine cells)	20.57	7.19	5.98	5.38	16.99	6.90	5.57	5.13
B. Marijuana								
Error correlation (ρ)	–	0.19	–	−0.20	–	0.17	–	−0.19
		(0.07)		(0.07)		(0.08)		(0.12)
Social interaction effect								
Intermediate level of activity (γ_1)	–	–	0.32	0.46	–	–	0.30	0.45
			(0.08)	(0.08)			(0.09)	(0.16)
High level of activity (γ_2)	–	–	0.10	0.25	–	–	0.08	0.21
			(0.12)	(0.04)			(0.13)	(0.20)
Log likelihood	−772.38	−770.00	−762.78	−761.72	−712.86	−711.25	704.79	−703.96
Goodness of fit (nine cells)	37.40	24.11	2.84	1.86	32.45	24.17	3.76	1.93
C. Truancy								
Error correlation (ρ)	–	0.33	–	0.17	–	0.33	–	0.17
		(0.06)		(0.14)		(0.07)		(0.15)
Social interaction effect								
Intermediate level of activity (γ_1)	–	–	0.31	0.18	–	–	0.30	0.17
			(0.07)	(0.14)			(0.07)	(0.14)
High level of activity (γ_2)	–	–	0.28	0.15	–	–	0.26	0.14
			(0.10)	(0.13)			(0.10)	(0.14)
Log Likelihood	−980.36	−968.39	−967.34	−966.43	−952.10	−941.31	−940.43	−939.57
Goodness of fit (nine cells)	37.55	7.64	7.07	4.38	32.52	7.78	6.64	4.55

See note to table 3. Standard errors clustered by school in parentheses. Sample sizes are 738 for panel A, 1,076 for panel B, and 964 for panel C. In each case, the sample includes only pairs in which neither friend had engaged in the intermediate or higher level of the risky behavior as of wave 1.