Peer Effects and Multiple Equilibria in the Risky Behavior of Friends

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February 2012

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 in the first wave of the survey, we estimate bivariate ordered choice models for their subsequent decisions that include peer effects and unobserved heterogeneity. We find significant interaction effects in sexual initiation: the likelihood that one friend initiates intercourse within a year of the baseline interview increases by almost 5 percentage points (on a base rate of 11%) if the other also initiates intercourse, holding constant a wide set of individual and family factors. Similar effects are also present for smoking, marijuana use, and truancy. We find larger peer effects for females, and large asymmetries in the strength of the effects in non-reciprocated friendships.

We have benefited greatly from the suggestions of two anonymous referees. We also thank Ana Rocca for outstanding research assistance, and Peter Arcidiacono, Philip Babcock, Pat Kline, Justin McCrary, and seminar participants at UC Santa Barbara, Duke University, UCLA, and the University of Miami for many helpful suggestions and comments.

This research uses data from Add Health, a program project directed by Kathleen Mullan Harris and designed by J. Richard Udry, Peter S. Bearman, and Kathleen Mullan Harris at the University of North Carolina at Chapel Hill, and funded by grant P01-HD31921 from the Eunice Kennedy Shriver National Institute of Child Health and Human Development, with cooperative funding from 23 other federal agencies and foundations. Special acknowledgment is due Ronald R. Rindfuss and Barbara Entwisle for assistance in the original design. Information on how to obtain the Add Health data files is available on the Add Health website (http://www.cpc.unc.edu/addhealth). No direct support was received from grant P01-HD31921 for this analysis.

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 and Vuong, 1984; Bajari, Hong and Ryan, 2009).

[1] For example, studies have analyzed quasi-experimental variation in neighborhoods (e.g. Oreopoulos, 2003; Jacob, 2004; Kling, Liebman, and Katz, 2007), classmates (e.g. Argys and Rees, 2008; De Giorgi, Pelizzari and Redaelli, 2010); college roommates (e.g. Sacerdote, 2001; Zimmerman, 2003; Kremer and Lavy, 2008; Stinebrickner and Stinebrickner, 2006); and squadrons in the U.S. Air Force Academy (e.g. Carrell, Fullerton and 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 and Tamer (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 also collected a rich set of individual characteristics—including measures of physical development, for example —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 allow 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 percent) if the other also initiates intercourse, 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

[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 (2006), Bramoulle, Djebbari and Fortin (2007), and Halliday and Kwak (2009).

[5] The Ali, Mikhail, and Haq (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).

models in which all the covariates of one friend are allowed to directly affect the choices of the other (i.e., 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 but very small differences by age.[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 (see e.g., 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 (e.g., intimate touching in the case of sex), and y=2 as a higher level of participation (e.g., 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

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

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 (e.g., 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]

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

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

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:

$$y_i = 0 \quad \text{if} \quad y_i^* \leq c_1,$$

$$y_i = 1 \quad \text{if} \quad c_1 < y_i^* \leq c_2,$$

$$y_i = 2 \quad \text{if} \quad y_i^* > c_2.$$

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 $F(\varepsilon_i)$.

[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.

Interaction effects in the thresholds allow the choice probabilities for friend #1 to depend on the actual choices of friend #2 and vice versa. The choices of the two friends can then be represented by a bivariate ordered choice system:

(2) $$y_i^* = X_i\beta + \varepsilon_i ,$$

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

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) are distributed as bivariate normal with correlation ρ. As an alternative we consider a correlated bivariate logistic distribution based on the copula function proposed by Ali, Mikhail and Haq (1978).

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

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

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

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, below, and find that the restrictions implied by (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 (ε_1, ε_2) space that maps into the 9 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 is treated as the main outcome of interest and the two

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[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 $c_2(y)$ only depends on 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 X's and (ε_1, ε_2). We do not consider mixed strategy equilibria.

lower levels are pooled, Figure 1 collapses to the simpler partition associated with a bivariate discrete choice game analyzed by Soetevent and Kooreman (2006, Figure 1). 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 and 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., $(y_1, y_2) \in \{(0,0), (1,1), (2,2)\}$. 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

[12] One justification for the restrictions in (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, Hong and Ryan (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 suggested by Tamer (2003), which uses estimates of the probabilities for two of the three outcomes that can arise from regions of multiplicity (e.g., $p((y_1, y_2) = (1,1) \mid X_1, X_2)$ and $p((y_1, y_2) = (2,2) \mid X_1, X_2)$.

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) 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 (i.e., 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 discussed in detail by Heckman (1978; 1981) and Hyslop (1999), 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 hetereogeneity 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 (DGP's): (1) a DGP with social interaction effects but no correlation in the unobserved error components (i.e., γ_1>0, γ_2>0, ε_1 and ε_2 uncorrelated normal variates); (2) a DGP with correlated unobserved heterogeneity but no social interaction effects (i.e., γ_1=0, γ_2=0, ε_1 and ε_2 correlated normal variates with correlation ρ); (3) 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 DGP's 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 below we present two additional robustness checks that utilize 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). This study collected longitudinal information for a sample of U.S. adolescents who were in 7th-12th grades in the 1994-95 school year (see Harris et al., 2009), including unique information on the friendship networks between sample members. The sample frame for the study included a random sample of 80 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: a total of 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 from the Wave 1 and Wave 2 in-home surveys.[16] Importantly, the Add Health sample design included 16 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

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

[16] The main loss of sample between Wave 1 and Wave 2 arose from the graduation of 12th-grade students. Graduates were not re-interviewed unless they had younger siblings in the school.

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 non-saturated 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 "non-reciprocated" 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 sub-sample of 738 friend-pairs with minimal sexual experience as of the Wave 1 interview.[20] (In Section VI below, we address potential concerns associated

[17] We include non-responders to the in-school questionnaire, who represent about 20% of our sample.
[18] We give primacy to the in-home interview both 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 (i.e. those who completed the in-school questionnaire and/or were in a saturated school) 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 if 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 18 months, and to

with this sample selection rule). We use Wave 2 data to classify sexual experience one year later into 3 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 who were not regular smokers, and high-intensity smokers as those who smoked regularly—that is, at least one cigarette every day for 30 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 30 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 is based on Wave 1 responses to 3 gender-specific questions on physical development. We convert the answer to each question to a z-score and take the average.
- Attitude toward risk is based on strength of agreement with the statement “You like to take risks.”[22]

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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.

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

- Future orientation is based on agreement with the statement: "You live your life without much thought for the future." This is reported on a scale from 1 (strongly agree) to 5 (strongly disagree).
- Time preference is 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 is 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 is a dummy for the presence of two parents as of Wave 1.
- Frequency parents attend church is 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 are based on Wave 1 reports of parental education. We classify families with 2 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 (e.g., 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 in the upper panel 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 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 middle panel 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 20-40% range, but are lower for the subsamples with limited sexual experience.

Finally, the bottom panel 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 zero to 22% for intimate contact and from zero to 14% for intercourse.

Appendix Table 2 shows the means for subsamples with minimal participation in each of the other risky behaviors as of Wave 1. The initiation rates for other risky activities 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 10-50% 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 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 9 possible outcomes. (Coefficients and standard errors for the covariates are reported in Appendix Table 3). We present four specifications: a benchmark model with neither correlated heterogeneity nor social interaction effects (i.e., $\rho= \gamma_2= \gamma_1=0$) in columns 1 and 5; a model with only correlated heterogeneity (i.e., $\gamma_2= \gamma_1=0$) in columns 2 and 6; a model with only social interaction effects (i.e., $\rho=0$) in columns 3 and 7; and a general model in columns 4 and 8. The specifications in columns 1-4 include our baseline set of individual and family characteristics, while the models in columns 5-8 include the baseline covariates plus 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, 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 for 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 (i.e., 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.

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 sizeable, and suggest that peer behavior exerts an important influence on sexual initiation behavior of teenagers. Specifically, the likelihood of initiating intercourse increases by 4.9 percentage points (on a base rate of 11 percent) 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 percent) 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 (see Appendix Table 3). 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,

[23] For comparison purposes, the simple chi-squared statistic for the outcomes of the pairs across the 9 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.

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 specifications in columns 5-8 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:

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

or:

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

The average probabilities of these two conditions occurring in our sample are 4.7% and 4.9% respectively, which are 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 (i.e., her friend is not affected by her choice but she is in a region of influence); and for cases of bi-directional influence (where 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 (e.g. when one chooses to initiate a higher level of intensity because her friend does) and cases where the friend has a "moderating" influence (e.g. when one stays at the lower level of intensity because her friend also does).

On average, when peer influence occurs, one friend is either highly unlikely or highly likely to

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[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 $P(\varepsilon_i > c_{20} - X_i\beta - \gamma_2)$.

initiate sex, and therefore exerts a uni-directional influence on her friend. Less than 1 percent of the population falls in the regions of multiple equilibria (regions A or B in Figure 1) where the influence is bi-directional. 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 percent 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 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:

[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 7 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.

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

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

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 $\gamma_{21}=0$.

Appendix Figure 1 shows the partition of (ε_1, ε_2) space corresponding to the generalized model under the assumptions that $0 \leq \gamma_{j1} \leq \gamma_{j2}$ and $c_{10} \leq c_{20} - \gamma_{22}$. There are now 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 general model assuming that the threshold coefficients satisfy the ordering in Appendix Figure 1, 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 (ρ=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 (i.e., 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 (b). 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.

V. Robustness Tests

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

a. Models that assume a fixed value for rho

In the sections below, 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 non-negative (Table 2). Under this assumption, the estimates of γ_1=.20 and γ_2=.27 from our baseline model with ρ constrained to equal zero (Table 3, col. 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 non-randomly, 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 likelihood 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 ρ=0.06 (consisent with the results in col. 4 of Table 3). At the upper limit we obtain a small positive social interaction effect for the high level of sexual activity (γ_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 ρ=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 non-overlapping groups of potential best friends. Controlling 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 γ_1=0.05 and γ_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 zero. 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 1-4 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 (i.e., γ_1=γ_1=0). Moreover, allowing for unobserved heterogeneity greatly improves the fit of the model (compare columns 5 vs. 6 and 7 vs. 8) whereas the inclusion of social interaction effects does not (compare columns 5 vs. 7 and 6 vs. 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 normal to a generalized bivariate logit distribution. We use the copula function proposed by Ali, Mikhail, and Haq (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:

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

where $\theta \in [-1, 1]$ is a measure of association.[28] As shown by Kumar (2010), 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 τ=0 when θ=0.[29]

Estimation results for bivariate ordered logit models are presented in Table 8. For reference the first 4 columns of the table reproduce the ordered probit models in columns 1-4 of Table 3. Columns 5-8 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 be roughly 2 times bigger than the corresponding probit coefficients.

Comparisons between the corresponding columns of Table 8 show that inferences about the

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[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 θ=0.

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 (θ=1, corresponding to τ=0.33) there is a sizeable 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 check the robustness of our results to this assumption by estimating models without any exclusion restrictions. Here, the estimates of ρ, γ_1 and γ_2 are driven entirely 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.

The results of these tests are summarized in Table 9. In the specifications that include all *X*'s of 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 model 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. However, the estimates of the gammas are very similar to those in columns 3 and 4. Again we interpret these results as confirming the relative robustness of our baseline estimates.[30]

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 estimate a two-step selection model (Heckman 1979) in which the first stage is a simple probit model for the probability of being in our estimation sample. This model includes all the baseline characteristics of *both* friends (a total of 32 variables) and is estimated on the full sample of 1,689 matched friend pairs.[31] Appendix Table 4 shows estimates from models similar to those in Table 3, but which include a selection correction term (the estimated inverse Mills ratio) from the first stage as an additional regressor. The estimated coefficient on the selection term is uniformly insignificant across the models, with a positive sign in the models with only our baseline covariates and a negative sign in models with the extended covariates. Importantly, however, the estimates of ρ, γ_1, and γ_2 are almost identical to those in Table 3, leading us to conclude that any sample selection biases in these critical coefficients are small.

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

[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 Appendix Table 4a).
[31] The selection correction term in the second stage model is therefore identified by excluding the friend's covariates from the outcome equation.

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 or not the friendship is reciprocated.

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

(5a) $\gamma_1 = \exp(a + bZ)$,

(5b) $\gamma_2 = \exp(c + dZ)$.

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 (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 sexual intercourse. However, we find no evidence of heterogeneity in peer effects by age (column 2).[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

[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.
[33] It is worth noting that in our sample, older friend pairs are arguably less representative of their peers, since sexual experience tends to increase with age. Hence the lack of heterogeneity in peer effects by age provides further evidence that our estimates are not much affected by restricting the sample to pairs with minimal sexual experience.
[34] We use a predicted measure of friendship stability instead of an *ex post* measure because the stability of the friendship may itself 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 principal, 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.

depend on whether or not she reciprocated the friendship nomination of her friend. The estimates imply large asymmetries. Indeed, they suggest that students who we assign to a friendship but who 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 estimates for our baseline model (i.e., the model in column 4 of Table 3) fit separately for reciprocated and non-reciprocated 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 non-reciprocated pairs the corresponding increase is only about 2.5 percentage points. The model in column 3, which is fit only to the non-reciprocating pairs, allows different values of γ_1 and γ_2 for the *nominators* and the (non-reciprocating) *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 non-reciprocator 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 unfortunately, given the small sample sizes, we cannot make strong inferences.

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 Appendix Table 5 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 the results 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.[36]

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

[36] Our definition of "experimental" use is based on whether the respondent indicates having tried marijuana as of the Wave 2 interview, while our definition of "regular" use is based on whether the respondent indicates having used one or more times in past 30 days. Thus, respondents who tried marijuana for the first time in the past 30 days may be misclassified as regular users, while more regular users may be classified as experimental users if they went for 30 days without using.

of all 4 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 these flexible models and are relatively imprecise, the point estimates suggest that both factors may be present. Finally, the estimates of γ_1 and 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 Conclusions

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 non-reciprocated 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 non-reciprocator 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.

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Table 1. Descriptive Statistics for Various Samples

	Full Wave 1 & 2 Sample (1)	Same-sex Best Friend Pairs (2)	BFs with no touching or intercourse at Wave 1 (3)
Individual & 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 non-white 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
Freq. 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 1 parent finished high school	0.88	0.88	0.90
At least 1 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 1 or more days	0.27	0.26	0.13
Skipped school 2 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
Sex Experiences as of Wave 2:			
Intimate touching w/ 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

Notes: see text for description of algorithm for identifying best friend (BF) pairs.

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 (1)	Adjusted (2)	Raw (3)	Adjusted (4)
Individual & 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
Freq. parents attend church (0-3 scale)	0.28	0.24	0.32	0.31
At least 1 parent finished high school	0.34	0.33	0.38	0.36
At least 1 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 1 or more days	0.28	0.15	0.23	0.20
Skipped school 2 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

Notes: columns (1) & (3) show simple correlation coefficients between characteristics of best friends in each pair. Columns (2) & (4) show partial correlation coefficients that control for the gender, age, and race of both friends.

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	--	--	0.20	0.16	--	--	0.16	0.15
Level of Activity (γ_1)			(0.05)	(0.08)			(0.06)	(0.08)
Social Interaction Effect - High Level	--	--	0.27	0.22	--	--	0.23	0.21
of Activity (γ_2)			(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

Notes: standard errors, clustered by school, in parentheses. See text for model descriptions. Sample includes 738 friend-pairs with minimal sexual experience at Wave 1. Dependent variable is ordered variable indicating intimate touching, intercourse, or neither. Models in columns 1-4 include 2 constants and 16 other person-specific controls. Models in columns 5-8 include these controls plus Wave 1 GPA and 8 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 Appendix Table 3.

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	

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

Table 5: Estimated Probability that Choice of Sexual Activity is Influenced by Friend's Behavior, by 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
Sub-total	–	0.072	0.018	0.003	0.003	–
Sum of probabilities	0.906	0.090		0.005		1.000

Note: estimates based on simulations of model shown in column 4 of Table 3.

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)
Social Interaction Effect - 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)
Social Interaction Effect - 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)
Social Interaction Effect - 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

Notes: standard errors, clustered by school, in parentheses. See text for model descriptions. Sample includes 738 friend-pairs who had not engaged in intercourse or intimate contact by Wave 1. Dependent variable is ordered variable indicating intimate touching, intercourse, or neither. Models in columns 1 and 3 include 2 constants and 16 other person-specific controls. Models in column 2 and 4 include 16 same controls plus Wave 1 GPA and 8 additional dummies indicating level of experience in cigarette smoking, marijuana use, truancy, and alcohol use as of Wave 1.

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	--	0.14	--	0.19	--	0.19
		(0.07)		(0.11)		(0.07)		(0.07)
Social Interaction Effect -	--	--	0.23	0.12	--	--	0.11	0.00
Intermediate Level of Activity (γ_1)			(0.06)	(0.10)			(0.06)	(0.00)
Social Interaction Effect -	--	--	0.29	0.18	--	--	0.06	0.00
High Level of Activity (γ_2)			(0.08)	(0.10)			(0.08)	(0.00)
Attitude to Risk	0.13	0.12	0.13	0.12	0.13	0.12	0.13	0.12
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Physical Development Index	0.26	0.26	0.26	0.26	0.26	0.25	0.26	0.25
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Log Likelihood	-980.62	-971.42	-970.05	-969.35	-980.62	-976.74	-979.07	-976.74
Goodness of Fit (9 cells)	27.62	4.15	2.40	0.56	14.95	4.13	10.13	4.13

Notes: standard errors, clustered by school, in parentheses. Original estimation sample (columns 1-4) includes 738 friend-pairs who had not engaged in intercourse or intimate contact by Wave 1. False friends sample (columns 5-8) is constructed from the same set of respondents as the original sample, and includes 738 includes pairs of adolescents with similar propensities to initiate sexual activity (see text for details). Dependent variable is ordered variable indicating intimate touching, intercourse, or neither. All models include 2 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 3 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 zero.

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	--	--	0.20	0.16	--	--	0.35	0.27
Level of Activity (γ_1)			(0.05)	(0.08)			(0.11)	(0.19)
Social Interaction Effect - High Level	--	--	0.27	0.22	--	--	0.49	0.42
of Activity (γ_2)			(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	--	--	--	--	0.00	0.15	0.00	0.04

Notes: standard errors, clustered by school, in parentheses. See text for model descriptions. Sample includes 738 friend-pairs who had not engaged in intercourse or intimate contact by Wave 1. Dependent variable is ordered variable indicating intimate touching, intercourse, or neither. All models include 2 constants and 16 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 θ=0 implying uncorrelated errors. Bottom row of table shows implied rank-order correlation of latent errors of two friends, using formula from Kumar (2010).

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 X1s and X2s		No Excluded Variables - both equations contain only gender & avg. age
	(1)	(2)	(3)	(4)	(5)
Include Wave 1 Behaviors?	no	yes	no	yes	no
Effect of Excluded Variable on Individual Behavior	--	--	--	--	--
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- Interm. 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)
Social Interaction - 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

Notes: standard errors, clustered by school, in parentheses. See notes to Table 3. Models in columns 3-4 allow all *X* 's of each friend to affect the other. Model in column 5 controls only for the gender of the pair and their average age.

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	Indicator for respondents who did not reciprocate
	(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 (a)	-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 Prob. (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 Prob. (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

Notes: see notes to Table 3. Standard errors, clustered by school, in parentheses. All models include 2 constants and 16 person-specific controls. Models for peer effects are parameterized as: $\gamma_1=\exp(a+bZ)$, $\gamma_2=\exp(c+dZ)$: see text.

Table 11: Estimated Bivariate Ordered Probit Models, Fit by Subgroup

	Reciprocated Pairs Only	Non-Reciprocated Pairs Only - Symmetric Effects	Non-Reciprocated 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)	
Social Interaction Effect - High Level of Activity (γ_2)	0.33	0.11	
	(0.06)	(0.10)	
Social Interaction Effect - Intermediate Level of Activity (γ_1) - **Nominators**			0.10
			(0.12)
Social Interaction Effect - High Level of Activity (γ_2) - **Nominators**			0.17
			(0.12)
Social Interaction Effect - Intermediate Level of Activity (γ_1) - **Non-Reciprocators**			0.03
			(0.09)
Social Interaction Effect - High Level of Activity (γ_2) - **Non-Reciprocators**			0.05
			(0.12)
Log Likelihood	-319.6	-610.26	-609.87
N	265	473	473

Notes: See notes to Table 3. Standard errors, clustered by school, in parentheses. In non-reciprocating friend pairs, the **nominator** is the friend who named the other as his/her "best friend"; the **non-reciprocator** failed to name the nominator as his/her best friend.

Figure 1: Partition of (ε_1, ε_2) for Bivariate Ordered Probit

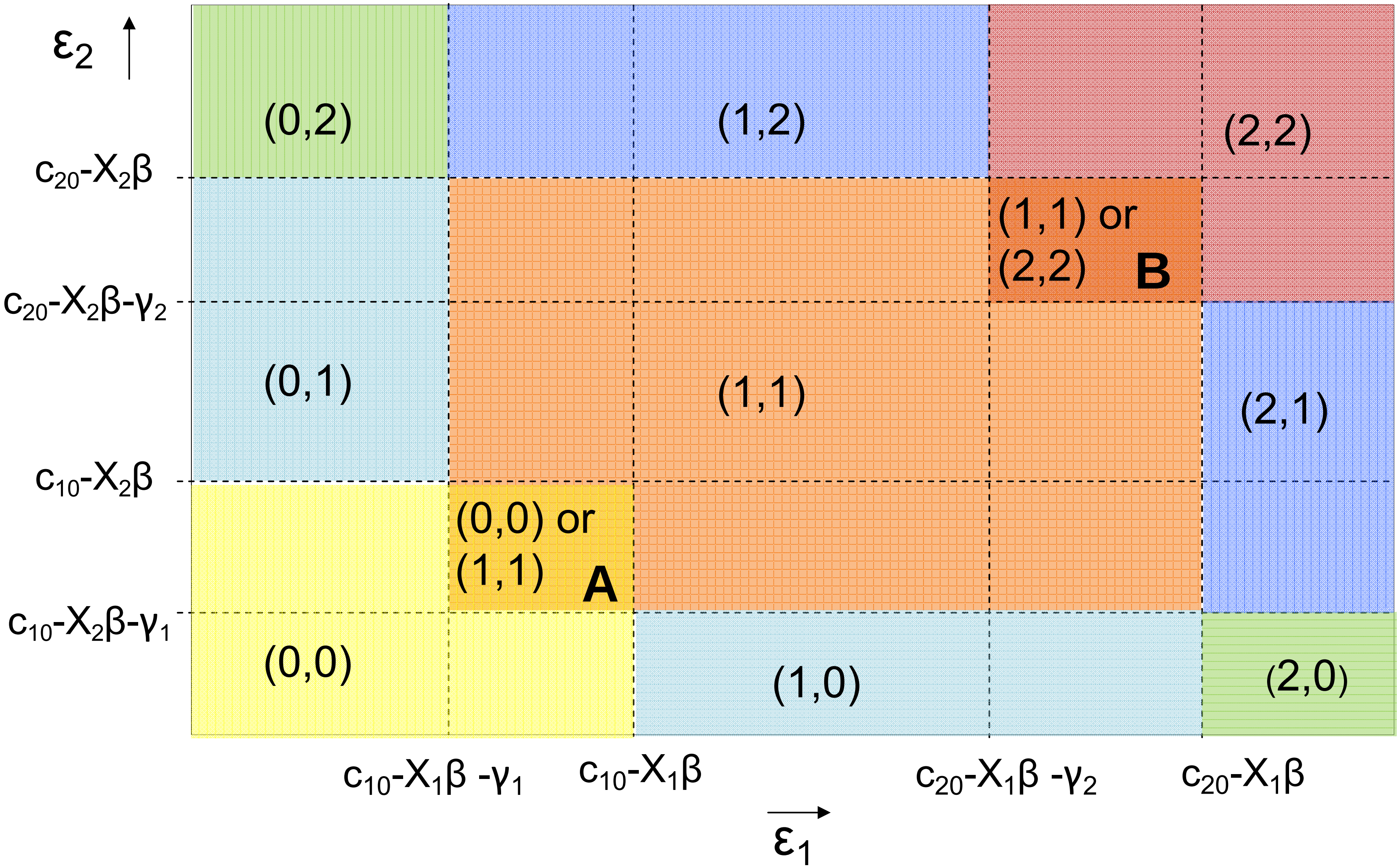
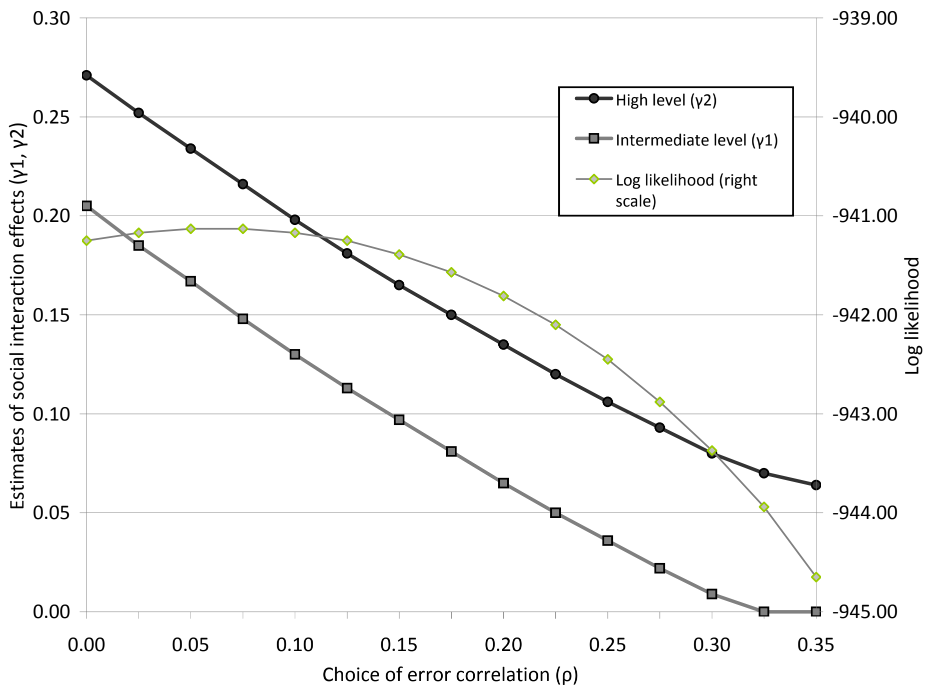
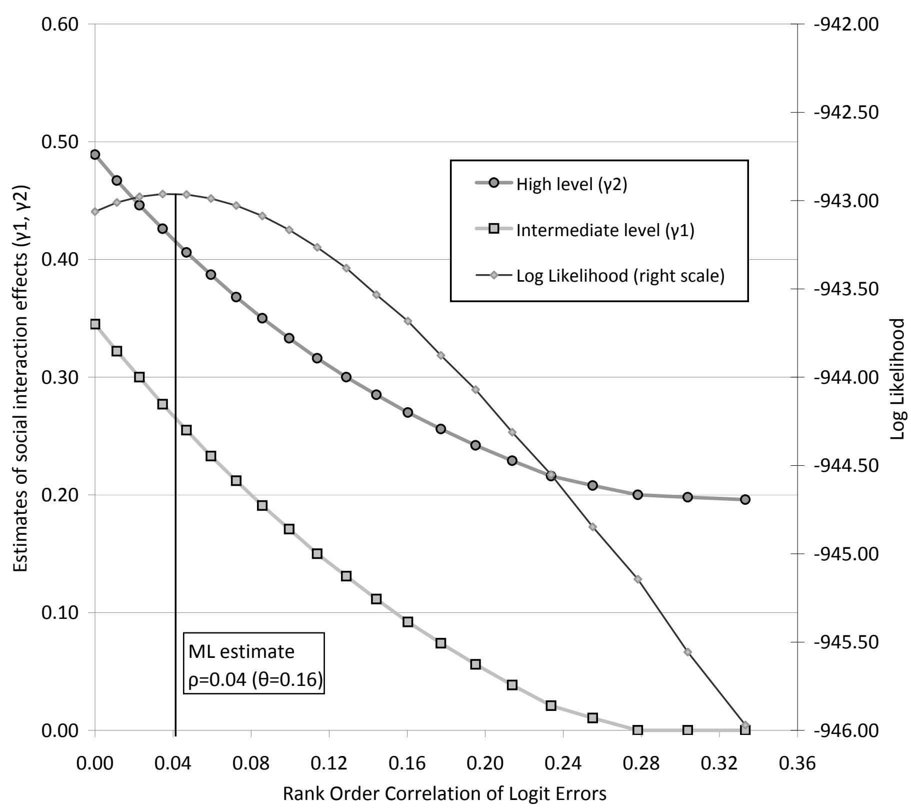


Figure 2: Estimates of γ_1, γ_2 and Maximized Log Likelihood for Alternative Choices of Correlation Parameter

A. Bivariate Probit Model



B. Bivariate Logit Model



Appendix – Description of 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 β=0.5 while in design #2 we choose β=0. The value of β=0.5 was selected to approximate the power of the observed covariates in our actual sample, which yield a pseudo-R-squared 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 equation (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 γ_1 =0.20, γ_2 =0.25 and ρ=0. For DGP #2 we set $\gamma_1 = \gamma_2 = 0$ and ρ=0.25. For DGP #3 we set γ_1 =0.10, γ_2 =0.15 and ρ=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 DGP's 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.

Appendix Table 1 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 1000 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.

Appendix Table 1: Empirical Distributions of Estimation Errors in Application of Bivariate Ordered Probits to Three DGP's, 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: γ_1=0.20, γ_2=0.25, ρ=0		
a. Median/Mean Error in γ_1	-0.01 / -0.02	0.00 / -0.02
(std. dev)	(0.09)	(0.11)
b. Median/Mean Error in γ_2	-0.02 / -0.02	-0.03 / -0.04
(std. dev)	(0.10)	(0.10)
c. Median/Mean Error in ρ	0.01 / 0.02	-0.02 / 0.02
(std. dev)	(0.10)	(0.13)
2. DGP #2: γ_1=0, γ_2=0, ρ=0.25		
a. Median/Mean Error in γ_1	0.00 / 0.02	0.00 / 0.03
(std. dev)	(0.03)	(0.05)
b. Median/Mean Error in γ_2	0.00 / 0.03	0.00 / 0.03
(std. dev)	(0.04)	(0.05)
c. Median/Mean Error in ρ	-0.02 / -0.02	-0.01 / -0.02
(std. dev)	(0.07)	(0.08)
3. DGP #3: γ_1=0.10 γ_2=0.15, ρ=0.15		
a. Median/Mean Error in γ_1	0.00 / 0.00	0.00 / 0.01
(std. dev)	(0.06)	(0.09)
b. Median/Mean Error in γ_2	0.00 / 0.00	-0.01 / 0.01
(std. dev)	(0.09)	(0.10)
c. Median/Mean Error in ρ	0.00 / 0.00	-0.02 / -0.03
(std. dev)	(0.08)	(0.09)

Notes: based on applications of maximum likelihood estimation of model with both unobserved heterogeniety and social interactions, with 100 simulations per DGP. See text for details on the design of the data sets used in the simulations. Simulated data has 1000 friend pairs.

Appendix Table 2. Descriptive Statistics for Samples Used in Analyses of Smoking, Marijuana Use, and Truancy

	BFs who had never smoked a cigarette as of W1	BFs who had never tried marijuana as of W1	BFs who did not skip any days of school in W1
	(1)	(2)	(3)
Individual & Family Characteristics			
Age (in years, as of wave 1)	15.51	15.50	15.39
Male	0.43	0.43	0.43
Black race	0.27	0.20	0.19
Other non-white race	0.18	0.16	0.13
GPA (1-4 scale)	3.00	2.97	2.99
Physical development index	0.03	0.07	0.08
Attitude toward risk (1-5 scale)	3.43	3.43	3.48
Future orientation (1-5 scale)	3.72	3.69	3.70
Time preference (1-5 scale)	1.50	1.53	1.52
Smokers in household (yes/no)	0.33	0.36	0.36
Two-parent household (yes/no)	0.73	0.74	0.75
Freq. parents attend church (0-3 scale)	1.97	1.92	1.88
Parents not religious (yes/no)	0.14	0.15	0.16
Parental church attendance missing	0.12	0.12	0.10
At least 1 parent finished high school	0.89	0.89	0.91
At least 1 parent finished college	0.43	0.41	0.43
Parental education missing	0.04	0.04	0.03
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 1 or more days	0.15	0.16	0.00
Skipped school 2 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 1 or more days			0.155
Skipped school 2 or more days			0.081
Number of observations	1,476	2,152	1,928

Notes: see text and notes to Table 1.

Appendix Table 3: Estimated Coefficients from Bivariate Ordered Probit Models for Sexual Activity by Friend Pairs in Table 3

	Baseline Covariates				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)
Freq. 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 1 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 1 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)
<u>Other Risky Behaviors at Wave 1:</u>								
Tried cigarette smoking					0.21	0.20	0.20	0.20
					(0.10)	(0.10)	(0.10)	(0.10)
Smoked cigarettes regularly					0.32	0.31	0.32	0.32
					(0.18)	(0.18)	(0.18)	(0.18)
Tried marijuana					0.12	0.12	0.11	0.11
					(0.17)	(0.17)	(0.17)	(0.17)
Used marijuana regularly					0.10	0.09	0.10	0.09
					(0.21)	(0.21)	(0.21)	(0.21)
Drank alcohol without adult presence					0.47	0.48	0.47	0.47
					(0.10)	(0.10)	(0.10)	(0.10)
Drank alcohol regularly					0.17	0.15	0.15	0.15
					(0.18)	(0.18)	(0.18)	(0.18)
Skipped school 1 or more days					0.37	0.37	0.36	0.36
last school year					(0.14)	(0.14)	(0.14)	(0.14)
Skipped school 2 or more days					-0.06	-0.07	-0.07	-0.07
last school year					(0.21)	(0.20)	(0.20)	(0.20)

Note: Entries are estimated coefficients of covariates for models in Table 3 -- see note to that table for description of models. Standard errors, clustered by school, in parentheses.

Appendix Table 4: Bivariate Ordered Probit Models for Sexual Activity by Friend Pairs - With Correction for Sample Selection

	Baseline Covariates				Expanded Set of Covariates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Include Wave 1 Behaviors?	no	no	no	no	yes	yes	yes	yes
Error correlation (ρ)	--	0.24	--	0.07	--	0.18	--	0.01
		(0.06)		(0.09)		(0.07)		(0.10)
Social Interaction Effect -	--	--	0.20	0.15	--	--	0.17	0.16
Intermediate Level of Activity (γ_1)			(0.05)	(0.08)			(0.06)	(0.09)
Social Interaction Effect -	--	--	0.27	0.22	--	--	0.23	0.22
High Level of Activity (γ_2)			(0.06)	(0.09)			(0.06)	(0.10)
Selection Correction Term (based on	0.10	0.11	0.02	0.04	-0.09	-0.08	-0.15	-0.15
estimates from first stage probit)	(0.17)	(0.17)	(0.17)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
Log Likelihood	-949.55	-943.43	-941.07	-940.94	-893.89	-890.69	-888.28	-888.28
Goodness of Fit (9 cells)	20.85	4.35	1.70	0.84	12.65	4.47	0.71	0.65

Note: See notes to Table 3. In addition to controls included in models in Table 3, models in this table include a selection term (inverse Mills' ratio) estimated using coefficients from first stage probit model for neither friend having engaged in sexual activity as of Wave 1, estimated using the full set of 1689 friend pairs in the Wave 1- Wave 2 sample. The selection model includes controls for each friend's baseline characteristics (32 controls total).

Appendix Table 5: Summary of Bivariate Ordered Probit Models for Risky Behaviors of Friend Pairs

	Baseline Covariates				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	--	--	0.20	0.12	--	--	0.18	0.10
Level of Activity (γ_1)			(0.09)	(0.13)			(0.10)	(0.14)
Social Interaction Effect - High Level	--	--	0.44	0.36	--	--	0.44	0.35
of Activity (γ_2)			(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 (9 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	--	--	0.32	0.46	--	--	0.30	0.45
Level of Activity (γ_1)			(0.08)	(0.08)			(0.09)	(0.16)
Social Interaction Effect - High Level	--	--	0.10	0.25	--	--	0.08	0.21
of Activity (γ_2)			(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 (9 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	--	--	0.31	0.18	--	--	0.30	0.17
Level of Activity (γ_1)			(0.07)	(0.14)			(0.07)	(0.14)
Social Interaction Effect - High Level	--	--	0.28	0.15	--	--	0.26	0.14
of Activity (γ_2)			(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 (9 cells)	37.55	7.64	7.07	4.38	32.52	7.78	6.64	4.55

Notes: see notes to Table 3. Standard errors clustered by school in parentheses. Sample sizes are: 738 for panel A; 1076 for panel B; 964 for panel C. In each case, sample includes only pairs in which neither friend had engaged in the intermediate or higher level of the risky behavior as of Wave 1.

Appendix Figure 1: Partition of (ε_1, ε_2) for Generalized Bivariate Ordered Probit